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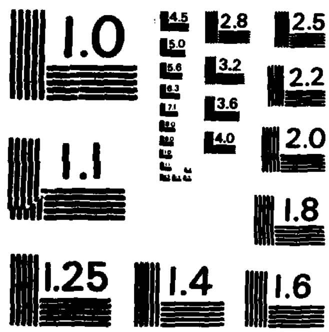

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REPORT ON THE EVALUATION OF DEMAND FORECASTING TECHNIQUES FOR THE SUBSISTENCE COMMODITY VOLUME I

DEPARTMENT OF DEFENSE

DEFENSE LOGISTICS AGENCY

Cameron Station
Alexandria, Virginia 22304-6100

Operations Research and Economic Analysis Office

OCTOBER 1985

Report on the Evaluation of Demand Forecasting
Techniques for the Subsistence Commodity
Volume I of II

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FOREWORD

This study involves the evaluation of quantitative techniques to improve subsistence demand forecasting in the Defense Logistics Agency. A wide variety of techniques were tested for approximately 4,000 item/warehouse demand series over the 1977-1983 time frame.

The range of forecasting techniques analyzed included the following: autoregressions, autoregressions with seasonal terms: simple moving averages; single, double, adaptive and combined exponential smoothing; naive and the current DLA methods. The methodology, in effect, substituted individual and/or groups of methods for the DLA method to compute forecasts over the 1980-1983 period.

Findings indicated that about 20% more variability in lead time demand was incurred during the 1980-1983 time period than achieved by a group of five methods identified in this study, during that period. Similarly, 14% more variability in procurement cycle demand forecast error was incurred during the 1980-1983 time period.

Procedures are identified that can achieve further substantial reductions in variability of lead time demand through the use of forecast adjustments. A prototype subsistence demand forecasting system is described based on the recommended group of models in this study. This study also serves as the analytical basis for the development of the functional description for the Forecasting Module of Defense Integrated Subsistence Management System (DISMS).

Volume I contains the body of the study report, while Volume II provides amplifying details in appendices.

The effort documented herein was a study; its findings and conclusions reflect the data at the time the study was conducted and should not be construed as the official position of the Defense Logistics Agency.

ROGER C. ROY
Acting Assistant Director
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Executive Summary

One of the primary missions of DLA is to provide supplies for hundreds of thousands of lines of inventory to customers in the Military Services, other Federal Agencies, and friendly foreign governments. Among those supplies is food or subsistence supplies. Paramount to the proper execution of the supply mission is the decision of when and how much to buy for replenishment of the DLA inventory in anticipation of customer demand. The validity of that decision depends on the Agency's ability to forecast customer demand.

Forecasting can either be qualitative or quantitative. Quantitative forecasting is the subject of this report. The techniques of quantitative forecasting begin with past data values and, following a systematic procedure, develop a prediction of future data values. The Defense Logistics Agency (DLA) uses quantitative forecasting to predict customer demand.

In 1980, DLA embarked on an effort to improve demand forecasting for the Subsistence commodity. This study concludes the analysis portion of that effort. The objective of the study was to investigate techniques for improving demand forecasts over lead times and procurement cycles.

In inventory management, the lead time is the length of time between the decision to replenish the item and the actual addition of its order quantity to the inventory. The procurement cycle is the length of time between successive buys. Safety levels represent extra inventory held as buffers against errors in demand and lead time forecasts. Demand forecasting links actual customer requirements and ordering habits (outside DLA's control) to these inventory levels held in anticipation of customer demand (within DLA's control).

Consequently, DLA's ability to accurately forecast demand or sales directly impacts on its mission performance. Specifically, improved forecasting will result in the following:

- o Improved customer service by enhancing management's ability to order the proper quantity of the right items at the right time.

- o Reduced safety stocks required to meet customer requirements. (DLA presently maintains safety stocks of $95 million (end FY 84) for Subsistence.)

- o Reduced risk of acquiring items in "long supply," less waste, merchandising stock at less than cost and other associated inventory costs.

On the other hand, inadequate forecasting results in the following:

- o Increased management effort required to meet customer requirements.

- o Increased operational costs due to spot buying and higher stock levels.

- o Increased risks of acquiring long supplies of materiel and the subsequent resource expenditures needed to manage the materiel.

Presently, DLA does not have perfect information on the factors that drive customer demands. Wide swings in demand due to special customer requirements can not be predicted by quantitative forecasting. However, quantitative

forecasting can be employed to minimize the variation between forecasted and actual demands of a recurring nature.

As stated before, the purpose of this study was to evaluate and test quantitative forecasting techniques to better plan for the replenishment of inventories for the Subsistence commodity. A primary reason for the initiation of the study is the existence of seasonal demand patterns in the subsistence commodity. Seasonal patterns occur when demand fluctuates in a similar way within a certain period (annually, quarterly, etc). Seasonality is not considered under present subsistence forecasting methods. About 1 out of 7 subsistence lead time demand series exhibit a seasonal pattern.

The approach to this study involved the following steps:

- Structuring historical demand data for the purpose of forecasting.
- Fitting various forecasting models based on 1978-1979 demand data.
- Evaluating those models based on the forecasted vs. actual demand for 1980 - 1983 demand data.
- Selecting the best individual model and or group of models for possible implementation.
- Testing methods to track forecast errors so that the models can be switched within the group. This is necessary when the assigned model no longer is tracking the demand pattern.

Analytical efforts of this study involved processing 7,850 subsistence demand series through more than 100 forecasting models. Complete documentation and explanation of tested forecasted models are included in the main study report.

The key findings of this study are as follows:

- Over the 1980 - 1983 time frame, the standard deviation of lead time demand derived from the current DLA forecast model was 20% larger than the standard deviation of lead time demand derived from a group of five alternative models.
- The group of five models includes two seasonal models which would provide the capability to forecast seasonal demands within the subsistence commodity.
- A new tracking signal was identified which responds more effectively to demand variation and provides the criterion for forecast model selection within the group.
- The recommended model group can be implemented as the Demand Forecasting Module for Management Requirements Determination under the new Defense Integrated Subsistence Management System (DISMS). The Demand Forecasting Module provides DISMS with the capability to develop, evaluate, compare, and control demand forecasts for the subsistence commodity.

Based on these findings, the Executive Director for the Directorate of Supply Operations should develop an implementation plan to incorporate the prototype forecasting system in this report into a Forecasting System Module for Management Requirements Determination under DISMS. The implementation costs are small when considered against the benefits gained. Specifically, these benefits include:

- Less safety stock to meet customer requirements.
- Reduced need for "crisis" management due to stockouts.
- Improved customer satisfaction.
- Less merchandizing of short shelf-life materiel.

In summary, DLA relies on customer requirements to schedule the timing and quantity of buys. For the subsistence commodity, seasonal patterns occur in 14% of item lead time demand distributions. Significant reductions in subsistence demand variation can be achieved through the replacement of present subsistence forecasting methods. The recommended model group can be expected to provide around 20% better lead time demand forecasts than existing methods. Moreover, the recommended tracking signal will provide more responsive warnings to management when demand patterns change. The application of quantitative forecasting techniques to the subsistence commodity, while not a panacea, can significantly improve the inventory management of that commodity. The implementation of these techniques in a Forecasting System Module serves as a major step toward the future in the development of the new Subsistence Requirements Determination System.

I. INTRODUCTION

A. Background

1. What is Forecasting. Forecasting is the prediction or estimation of future events and is an invaluable component of business planning. Effective planning sets goals and objectives for an organization and the strategies to attain these goals. Forecasting provides the benchmarks by which plans and policies can be developed to respond to future opportunities and problems. In business, better forecasts are needed since decisions usually involve dollars and the successful performance of a mission.

2. Specific Tasking. One of the primary missions of DLA is to provide supplies for hundreds of thousands of lines of inventory to customers in the Military Services, other Federal Agencies, and friendly foreign governments. Among those supplies is food or subsistence supplies. Paramount to the proper execution of the supply mission is the decision of when and how much to buy for replenishment of the DLA inventory in anticipation of customer demand. The validity of that decision depends on the Agency's ability to forecast customer demand.

Forecasting can either be qualitative or quantitative. The selection of a qualitative or quantitative technique depends on the specific application as well as on the information available to formulate a forecast.

Qualitative forecasting is best suited to those situations in which historical data is not readily available or applicable and in which judgement must be heavily relied upon. It is used to forecast changes in processes which may be the result of exogenous influences. Qualitative techniques are often applied only to long term situations due to their dependence on expert judgement and subjectivity.

Quantitative forecasting is the subject of this report. The techniques of quantitative forecasting begin with past data values and, following a systematic procedure, develop a prediction of future data values. With the onset of computers, application of quantitative forecasting has become widespread. Quantitative techniques have a track record of better accuracy and lower cost, and are generally accepted over qualitative techniques. Many quantitative techniques have been developed and applied by Government and industry to uncover the basic patterns of historical data in order to develop forecasts. Monitoring methods which send a signal to management when these patterns change are critical to the application of quantitative forecasting.

In 1980, the DLA Operations Research and Economic Analysis Office (DLA-LO) was tasked to discover what forecasting techniques should be applied for subsistence items. As a substantial number of subsistence items possess seasonal demand patterns, various forecasting methods not presently used by DLA had to be investigated. An objective of the tasking was to identify those item/demand characteristics that result in the assignment of a specific forecasting technique for established items. Based on this assignment, decision rules for assigning forecasting techniques to new items could be established. After initial review of the problem, the Defense Logistics Agency (DLA) contracted with Inductive Inference, Incorporated, to identify and test new techniques for a small sample of subsistence items. The test was successful and a report documenting the results was provided in October 1982 (Reference 13).

The DLA is currently implementing a plan for the worldwide integrated management of wholesale subsistence stocks. The Defense Personnel Support Center (DPSC), a primary level field activity of DLA, is the inventory control point for the subsistence commodity. The Defense Integrated Subsistence Management System (DISMS) encompasses all automated information systems that support subsistence management. As such, the design quality and integration of DISMS is critical for the success of this plan. Moreover, demand forecasting is a primary component in the management requirements determination process under DISMS.

In March 1983, the DISMS task group delivered the final Management Requirement for Forecasting which included the results of the contracted test. The DISMS Management Requirement for Forecasting demonstrated that better forecasting can be achieved through the decomposition of demand patterns into trend, seasonal, and random components. Also it was found that forecasting the lead time demand was better than developing a forecast based on a monthly forecast spread over the lead time.

DLA awarded a second contract to Inductive Inference, Incorporated in late 1983 to extend the techniques used in the first contract to the entire subsistence commodity and to identify patterns in item/demand/model assignment.

Due to the large volume of work involved and limited contract funding, DLA-LO employed a team approach with the contractor and DISMS task group and extensive support staff.

B. Statement of Problem. The demand forecasting techniques presently used by DPSC attempt to accurately track the underlying demand patterns for subsistence items. However, numerous statistical factors and policy influences exist that affect there patterns and complicate tracking. They are as follows:

1. Policy Influences - Created by management to enhance customer support or reduce cost, they include such actions as spot buys, promotional sales, item substitution, etc.

2. Statistical Factors -

a. Average Level - The underlying horizontal demand pattern which does not tend to increase or decrease in a systematic way.

b. Trend - The rate of growth or reduction in the average level of demand that is occurring from period to period.

c. Seasonality - Generally, recurring patterns at certain interval as a consequence of time of year. Examples are holiday items, ice cream, spareribs, cocoa, etc.

d. Cycle - Long-term (3-10 years) factors generally affecting the entire economy, heavily influenced by Government decisions and world politics.

e. Randomness - Represents all influences not included in level, trend, seasonality, and cycles. Includes such things as sampling error, acts of God, etc.

The problem is to identify forecasting methods which more accurately track

demand in light of these policy influences and statistical factors.

C. Objectives

The objectives of this study are:

1. To develop a prototype forecasting system to test and evaluate a variety of forecasting methods for the subsistence commodity.

2. To develop a set of decision rules to assign forecasting methods to new items in the subsistence inventory.

D. Scope

1. Project Effort. This study addresses a large scale test and evaluation of quantitative techniques for forecasting item/warehouse demands within the subsistence commodity. New techniques were identified that significantly reduce the forecast error and bias encountered with presently used methods. It is the intent of the authors that the methodology, findings, and conclusion of this study provide a first step towards the implementation of improved forecasting in DLA automated materiel management systems.

The study was limited in the following manner:

1. Monthly demand for stocked items at each subsistence wholesale depot for the period July 1977 - November 1983 (77 months) were extracted from the Defense Personnel Support Center (DPSC) files.

2. Each stocked item experiencing 48 months of nonzero demand for the period September 1979 - August 1983 was screened for further analysis (3,925 item/warehouse records).

3. Existing software developed under the previous contract study with Inductive Inference, Incorporated, was upgraded to increase its flexibility and power.

4. To provide management with information to assist in the decision of when and how much to buy, lead time demand forecasts and demand forecasts for the procurement cycle following the lead time were generated. No aggregation above the item/depot level was made.

5. Software was developed to augment forecast model identifications and estimations, to test model assignments to classes of items, and to evaluate forecast adequacy across the entire class of models. A group of models were recommended for final analysis and implementation.

An assumption of the study was that one hundred percent (100%) of nonrecurring demand for perishable items was included with recurring demand for forecasting at the wholesale level.

2. Report Organization The two volumes of this report document the work performed by the study team. Volume I, the Study Report, presents a general review of the study assignment, methodology, analysis, findings, and recommendations. Volume II addresses specific details about forecast model assignments for the subsistence commodity and the description of model formulas.

Section II of Volume I describes the current Subsistence commodity. The reader who has a general knowledge of the management subsistence may wish to bypass Part A, An Overview, and go directly to Part B; Demand Forecasting. The reader who has a comprehensive knowledge of subsistence and the role of demand forecasting may elected to skip Section II in its entirety.

II. THE SUBSISTENCE COMMODITY

A. An Overview

The availability of wholesome and popular food and foodstuffs (known as subsistence) both on the mess hall table and on the commissary shelf is critical to the health and morale of the U.S. Forces and their families. DLA has the mission to provide high quality subsistence to the Military Services, some Federal agencies, and authorized foreign governments.

1. Subsistence Categories

The subsistence commodity management is presently split into two categories: perishable and semiperishable. Perishable subsistence includes nonstocked items such as fresh fruits and vegetables, bread and milk and stocked items that require chilling or freezing. Semiperishable subsistence includes items that do not require chilling or freezing such as canned goods. Within the categories of perishable and semiperishable subsistence, items are classified as (1) troop issue - those generally intended for troop feeding and, to a minor extent, for commissary resale; and (2) brand name, those generally intended for commissary resale and, to a minor extent, for troop feeding. Brand name items are characterized by an alphabetic character in the seventh digit of the stock number.

Table 1 shows the primary federal supply classes (FSCs) that are managed under the subsistence commodity. Table 1 does not contain the FSCs for minor supermarket brand name semiperishable items, similar to convenience store items, such as flyswatters, brooms, light bulbs, etc. However, these items are stocked in the supply system and are included in this study.

The great majority of subsistence items occur in the following federal supply classes (FSCs):

Table 1

FEDERAL SUPPLY CLASSES FOR SUBSISTENCE

FSC	Title
8905	Meat, Poultry, and Fish
8910	Dairy Foods and Eggs
8915	Fruits and Vegetables
8920	Bakery and Cereal Products
8925	Sugar, Confectionary and Nuts
8930	Jams, Jellies and Preserves
8935	Soups and Bouillons
8940	Special Dietary Foods and Food Specialty Preparations
8945	Foods, Oils and Fats
8950	Condiments and Related Products
8955	Coffee, Tea and Cocoa
8960	Beverages, Nonalcoholic
8965	Beverages, Alcoholic
8970	Composite Food Packages
8975	Tobacco Products

2. Mission

The mission of subsistence commodity management within DLA is executed by DPSC's Subsistence Directorate (DPSC-S) through Subsistence Field Activities in CONUS and overseas, with support from certain Defense Depots, Military Service Activities, and Worldwide Integrated Management of Wholesale Subsistence Stock (WIMS) agents.

The customers for subsistence are mess halls and other base installations, and commissaries from which the items are resold to authorized buyers.

3. Special Characteristics. Some characteristics of the subsistence commodity which, in total, make it different from other commodities managed by DLA, are as follows:

a. Shelf Life Limitations. Useful life may be short and is variable; affected by handling and distribution.

b. Storage and Transportation. Refrigeration is required for many items; humidity must be controlled; piling is limited as is product mixing; high transportation per unit costs.

c. Product Utilization. "Fill or kill" requisition policy; low unit costs; high morale factor.

d. Product Availability. Depot shipment vs. direct vendor delivery vs. local purchase; seasonality of demand.

For morale and health purposes, it is necessary to provide a wide variety of subsistence products to the customer on demand.

4. Automated Materiel Management Systems

The DPSC uses three different automated systems to assist managers in providing logistics support to customers throughout the world. The Perishable Subsistence Automated Supply System (PSASS) is used to compute requirements, buy actions, and safety levels for perishable troop issue and brand name items overseas and perishable troop issue items in CONUS.

The Semiperishable Central Stocked System computes requirements, buy actions, and safety levels for semiperishable troop issue and brand name items overseas and semiperishable troop issue in CONUS.

The Direct Commissary Support System (DICOMSS) is used to provide direct supply support services for brand name items and items restricted to large commissary customers overseas but not supplied in CONUS. Within PSASS and the Central System, demand forecasts are generated which drive the timing and quantity of buys. Residual Stocks from DICOMMS shipments are held in the depots for future issue.

Further detail and illustrations on these management systems and subsistence requisition processing are provided in Appendix A.

B. Demand Forecasting

1. Demand Accumulation

DPSC stocks certain classes of items at the various depots to account for inaccuracy in demand forecasting, delayed contract deliveries, etc. Customer demands are supported either from storage or by direct vendor delivery. Demands which are less than a carlot are supported from depot stock and are used to generate forecasts. Customer demands that can be met with carlot shipments are supported by direct vendor delivery and are not used in demand forecasting.

In the semiperishable item Central Stock System, both recurring and 100 percent of nonrecurring demand are used in demand forecasting. In PSASS, only recurring demand is used. When a customer submits a recurring requisition for an item out of stock, the requisition is killed but the demand is stored. The demand forecasts used to develop stockage levels at the various depots are the subject of this section of the report.

2. Demand Forecast Computations. Monthly demand forecasts are computed for each location/type pack, as follows:

a. For both perishable chill and freeze items overseas and selected CONUS items, a three-month weighted average is calculated by adding two-thirds of the current month's demand to one-sixth of each of the past two months' demands. This is equivalent to a simple 4-1-1 moving average (known as the D-forecast).

Officially, for CONUS locations, purchases are made only for open funded requisitions for the past and current months (R-forecast) on the requisition status file. However, because other requisitions with short lead times may be received after the purchase is initiated, the 4-1-1 forecast is also applied for CONUS purchases and for safety level computations. General lack of confidence in both of these methods has led to item managers examining recent trends and this month's demand at the same time last year to estimate lead time demand, especially for brand name items.

b. Semiperishable subsistence is forecasted using single exponential smoothing with trend correction (modified double exponential smoothing). (See Appendix A for further discussion of the exponential smoothing techniques.) A general formulation for this method is:

The forecast $y_{t+m} = b_o + b_1$

where: $b_o = 2S'_t - S''_t$

$b_1 = (S'_t - S''_t)/(1 - \alpha)$

$S'_t = \alpha d_t + (1 - \alpha) S'_{t-1}$

$S''_t = \alpha S_{t'} + (1 - \alpha) S''_{t-1}$

d_t = demand for time period t

m = number of periods ahead to be forecast

α = weighting factor

Forecasts are computed for three alphas: .10, .15, and .20. For each forecast, the absolute deviation is computed as the absolute value of the difference between the last month's demand and the forecast of the last month's demand. The single exponential smoothed average of successive absolute deviations is designated as the mean absolute deviation (MAD). The alpha forecast, which yields the lowest MAD, is chosen to forecast future demand. Note that the DLA forecast is constant over all future periods.

c. Perishable fresh fruits and vegetables (FF&V) are forecast by the individual Defense Supply Offices (DSOs). Carlottable hardy FF&V are forecast using the demand for the same month a year earlier as adjusted by considering intangibles such as climatic conditions, fair market value, and increases or decreases in the number of personnel support. These forecasts are largely and necessarily subjective since such intangibles make a mechanical forecast impracticable. All other FF&V are purchased daily by field buyers to satisfy customer requirements received by telephone.

d. Item managers may override the mechanical forecasts for both perishable and semiperishable subsistence.

Table 2 summarizes the current demand forecast techniques for subsistence items and safety level computations.

Table 2

Demand Forecast Methods and Safety Level Computations for Subsistence

	Demand Forecast	Safety Level
PERISHABLE		
Overseas	D-Forecast = $\frac{4 D_t + D_{t-1} + D_{t-2}}{6}$ D_t = last month's demand	$\frac{1}{2}$ D - Forecast (15 days stock)
CONUS (Troop Issue Items)	Open funded requisitions (current and past month)	$\frac{1}{2}$ D - Forecast (15 days stock)
Exceptions (Some Brand Name)	D-Forecast = this period's demand last year (modified for recent trend)	$\frac{1}{2}$ D - Forecast (15 days stock)
SEMIPERISHABLE		Can be fixed at 0, 1/2, 1, 1-1/2 times the monthly forecast.
Overseas Troop Issue	Double Exponential Smoothing, α =.10, .15, or .20; Giving Least MAD	Can be variable; Service Level Function by NSN/Warehouse .5F $\leq$ VSL $\leq$ 1.5F
Brand Name	Double Exponential Smoothing, α =.20	at Oakland (NOS), = MAX (VSL, 2 x FILL QTY)[1]
CONUS Troop Issue	Double Exponential Smoothing, α =.10, .15, or .20; Giving Least MAD	at Norfolk (NNS), = MAX (VSL, 3 x FILL QTY)[1]
		at San Diego (NDS), Pearl Harbor (NPS), Charleston (NRS), = MAX (VSL, highest one month demand in last 6 months)

[1] FILL quantity refers to the Fleet Issue Load List stocked for Navy customers.

3. Unique Characteristics of Subsistence that Affect the Forecast

Subsistence item demands are independent in the sense that the demands are not driven by demand for "higher level" end items as are the demands for many hardware items. Subsistence demands tend to be continuous rather than lumpy. Subsistence item lead times and procurement cycles are short, averaging 4.5 and 1.5 months, respectively. The independence and continuity of subsistence demands and relatively short replenishment cycles improve the chances that quantitative forecasting methods can be applied to the commodity with success.

Finally, In subsistence inventory management, back orders are not filled. Therefore future demand is not dependent on past supply performance.

4. Use of the Demand Forecast

The demand forecast is used in subsistence inventory control systems to calculate procurement cycle demand, lead time demand, and safety levels. The sum of the lead time demand forecast and the safety level combine to make the reorder point which determines when to initiate a replenishment buy action. Presently, the procurement cycle and lead time demand are computed as the monthly demand forecast times the number of months in the procurement cycle period and lead time, respectively. The safety level computation is more complex (see Appendix I). Item managers frequently override the present machine-generated forecasts with their own calculations for seasonal and brand name items.

Safety stocks are needed to cover demand during the lead time when the actual demand exceeds the forecasted demand, the actual lead time exceeds the forecasted lead time or both. In subsistence inventory control, lead times are considered relatively constant and the emphasis is on the variation of demand over the replenishment cycle. If the actual demand exceeds the forecasted demand and safety level, then the customer will receive a substitute item or nothing at all. If the actual demand is less than the forecasted demand then inventory levels rise, increasing long supply, disposals and the merchandising of items at less than cost.

C. Description of the Demand Data Base. The present automated supply system for perishable subsistence maintains an on-line data store of twelve months of demand history while twenty-four months of history is held for semiperishable subsistence. Offline data stores of monthly demand history back to July 1977 are available for both categories of subsistence items. For this study, each item/ warehouse demand record with 48 months of nonzero demand beginning November 1979 for perishable items and September 1979 for semiperishable items was extracted and analyzed. The existing off-line DPSC demand data base which contains records from 1977 to 1981 did not record type pack information. Therefore, the demands were aggregated by type pack for each stock number by warehouse. The record layout is provided in Appendix C. A description of the record fields for each SN/warehouse location is provided in Table 3.

Table 3

ITEM/WAREHOUSE DEMAND RECORD FIELDS

Field	Description
SN	Stock Number (Brand Name - 7th character is alphabetic)
Type Pack	Domestic Pack = 1, Export Pack = 2 (Semiperishable only)
Depot Code	Three characters = semiperishable, two characters = perishables (See Tables 2 and 3)
Issue Code	Troop Issue = 1, Commissary Resale = 2
Supply Code	Item Supplied from Warehouse = 1, Item Supplied from Direct Vendor Delivery = 2
Item Number	Five digit code used as identification in lieu of SN
Procurement Cycle Period	Days between successive procurements
Lead time	Days between initiation of a buy action and receipt of the product at the depot
Fleet Code	Norfolk or Oakland = 1, Otherwise = 0 (Semiperishable only)
Chill Code	Chill = 1, Freeze = 2, Semiperishable = 9
Shelf Life	The period of time after production of an item during which it must be utilized
Safety Level Code	If VSL, code = 0 Fixed at 0 mos = 1 at 1-1/2 mos = 2 at 1 mos = 3 at 1/2 mo = 4
Unit of Issue	Designates the manner by which an item is issued such as jars, cans, bags, lbs.
Average Net Weight	Weight of product excluding packaging
Nomenclature	Short description of item
	Perishable Only
Recurring Demand Qty	From the customer's perspective, those demands that are regular in frequency
Nonrecurring Demand Qty	From the customer's perspective, those demands that are irregular in frequency

Table 3 (Continued)

Semiperishable Only

Troop Issue Demand	Demand supplied for troop feeding
Commissary Resale Demand	Demands supplied for resale in Military commissaries. The items demanded may be troop issue items as well as brand name

For this study, the demand were captured monthly from July 1977 through November 1983.

III. DEMAND FORECASTING METHODOLOGY AND ANALYSIS

A. An Overview. This section of the report describes the general philosophy and the methodology used to apply quantitative demand forecasting techniques to the Subsistence Commodity. Details are left to the appendices in Volume I and Volume II. Figure 1 provides an overview of the Demand Forecasting Methodology. There are six components to the methodology, as follows:

1. Forecasting System Design Considerations - This area describes the general environment and technical problems which must be surmounted in the design of the subsistence demand forecasting system.

2. Data Acquisition and Structuring - Data acquisition involves the determination of the number of demand observations and item characteristics needed to analyze subsistence demand patterns. In this study over 70 observations were available for most items/warehouse demand series so that it was feasible to identify and evaluate the underlying demand patterns. Data structuring involves the aggregation of monthly demands into lead time and procurement cycle sums and the notation used to predict future demands based on past demands over a predictor period. This predictor period may be the last month, last lead time or procurement cycle or any other specified period.

3. Forecasting Techniques - This area provides details on the identification and fitting of a wide range of quantitative forecasting methods to subsistence demand series.

4. Evaluation Criteria - This area describes the various statistical evaluation criteria used to rank the competing models.

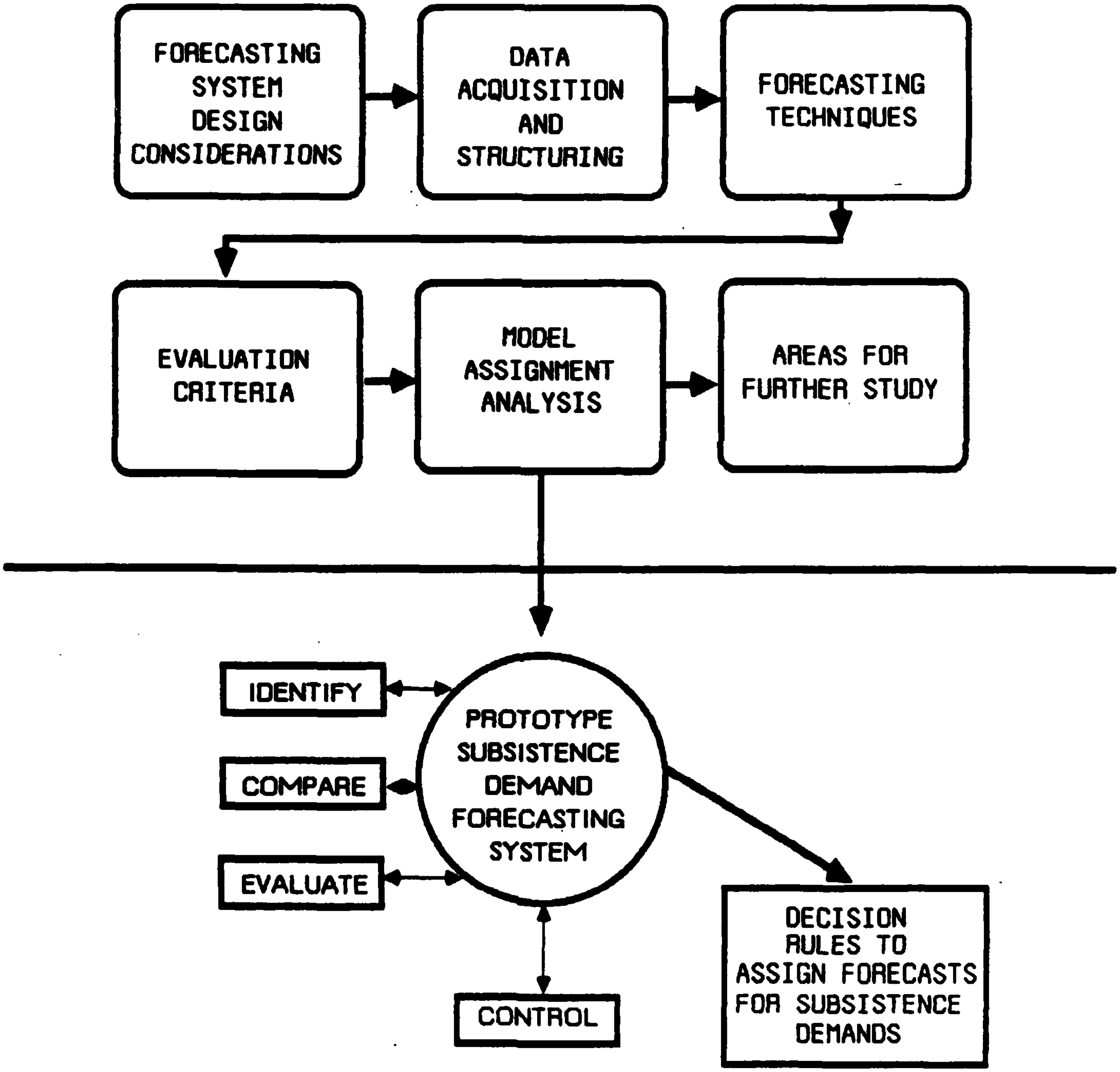
5. Model Assignment Analysis - This area involves the assignment of the best individual model and construction of the best group of forecasting methods for the subsistence commodity.

6. Areas for Further Study - This area involves suggestions for further study including adjusting forecasts based on the nature of the forecast error and monitoring forecast performance.

In the remainder of Section III, these components are described in more detail.

FIGURE 1

OVERVIEW OF DEMAND FORECASTING
METHODOLOGY AND ANALYSIS



B. Forecasting System Design Considerations

1. Requirements and Technical Difficulties. In designing a forecasting system for Subsistence, the following requirements and technical problems need be considered:

a. Need for Extended Forecasts. Common practice in inventory control is to forecast one period ahead, a month or quarter, and then to develop forecasts by multiplying the forecast by the number of periods in each lead time. However, this approach ignores any seasonality or trends in demand over the lead time. A better approach would be to forecast demand lead time and procurement cycle directly.

b. Need to Handle Large Numbers of Forecasts. Due to the special characteristics described in Section II, subsistence is managed by location; and accordingly forecasts are by item and location. Demand patterns for an item do vary by location, thereby necessitating separate forecasts for each location. There are approximately 40 locations and 4,000 items for a possible total of 160,000 forecasts. The actual number will be less since not every item is stocked at every location. However, since the number of required forecasts is large, techniques which cannot be automated are impractical.

c. Need to Limit Number of Forecasting Techniques. Due to the volume of forecasts, it is not practical to fit individual techniques to each item for each location. The preferred approach would be to find a point of diminishing returns where an increase in the number of techniques would not significantly improve forecast accuracy. Therefore, the number of techniques needs to be limited to the number that will not overload the automated system but still achieve significant improvements in forecast accuracy.

d. Bias in Selecting Techniques. Time series data is generally modeled by using the data both to identify the model (i.e., to determine its form) and to estimate its parameters. A series of models is selected (often by a stepwise procedure) and the parameters of these models are estimated in the data. The model that best fits the data (i.e., with the smallest error) is selected. Such a procedure produces a favorable bias in the error estimate that increases with the number of models considered. "Cross-validation" methods, where a portion of the series is witheld for evaluating the error, would produce no such bias. Such methods however are rarely used when the time series are not long, both because recent data is too important not to be used in model development and because of the extraordinary amount of computation that is require to systematically refit and test portions of the time series. Instead "Bayesian methods" that utilize a distribution of prior probabilities over the set of candidate models are sometimes used to obtain error estimates. More often, a model developed by the analysis of a relatively short time series is evaluated by using all points of a time series, first to estimate its parameters and second, to evaluate its forecasting errors (Reference 5).

e. Spurious Fits. The problems of bias described above are often manageable by the aforementioned techniques when a single time series is being fit. Here, however, a fundamental problem exists; models must be developed for many thousands of time series whose relation to one another is unknown. A model selected for a single time series may spuriously fit that series well. A number of the models so selected for many time series will almost certainly be spurious. Cross-validation of each individual model helps little--many models will most likely spuriously survive cross-validation. Even were such problems manageable, the use of conventional methods to develop models for so many series would be prohibitively cumbersome, time-consuming, and expensive.

f. Piggy-Backing Error. Another difficulty in using conventional methods to develop models that forecast the demands for subsistence items is that their computer realizations are designed for use in developing models that forecast the next point in a time series (i.e., next month's demand). When demand over a longer period is required, a technique called "piggy-backing" is used. Here the forecast point is treated as the last known data point and the next point is forecast. This is repeated until the required future time span has been forecast. This procedure unfortunately produces an error that rapidly increases with each repetition. Forecasts produced in this manner are generally useful only in forecasting the near future. In subsistence, the sum of the demands over a procurement cycle following a lead time (as well as the demand over the lead time) must be forecast for each item. Forecasts from two months to almost a year into the future are often required.

2. Approach Taken to Resolve Problems

a. Collection Versus Single Series Testing. A large number of models were tested against each demand series, those that fit these data best were identified (but not selected). However, recognizing that the performance of these models may be spurious, we selected models according to their performance on a collection of demand series rather than a single series. Each such collection will be defined in terms of characteristics of the items and their demand series. A single model will be used to forecast all demand series in each collection. The definitions of the collections will be developed by an analysis that assumes that a sufficient number of series are in each collection so as to maximize the precision of their corresponding models.

b. Division of Series for Development and Validation. Prior to the formation of the collections, those models that best fit each demand series were determined. A validation technique was used to estimate the forecasting error produced by each model. This estimate is not favorably biased. First, the initial 24 to 30 months of the time series (depending upon its length) were used to determine the parameters of the model. The following requisite demand (over lead time or procurement cycle) was then forecast and compared with the actual demand. Thereafter, for each point of the demand series, the parameters were evaluated using only the demands to that point, and a forecast was made and compared to the actual demand. This technique, produces a slightly unfavorably biased estimate of forecast error because only a portion of the series is used at each error evaluation.

c. Reorientation of Independent Variables. Rather than applying a "piggy-backing" technique for generating forecasts, the models used directly forecast either the sum of the demand over the lead time or the sum of the demand over the procurement cycle following the lead time (different models were used for each). That is, the dependent variables were such sums of demands and the independent variables were the monthly demands or a sum of demands over a specified predictor period. The least squares fits were performed using proprietary software in conjunction with a technique for algebraically operating on the demand series to automatically construct the requisite matrices. The software has proved sufficiently economical in computer usage so that it has been, thus far, possible to set the parameters of over 100 models approximately 36 times (i.e., 1 for each of 36 time periods) for both the lead time and procurement cycle forecasts for each of 3,925 item/warehouse demand series. This number of tests was used to estimate the errors produced by each model on each demand series.

C. Data Acquisition and Structuring. The central theme of quantitative forecasting is the assumption that some pattern exists in what has gone before and that the pattern will continue. Each forecasting technique makes explicit assumptions about the type of underlying pattern. The ability of a given technique to forecast effectively in a specific situation depends largely on the characteristics of the pattern. There are five types of basic patterns usually identified as follows:

1. Level is defined as the average of the demand values over a specific period of time.

2. Trend is defined as the growth or decline occurring in demand values over time.

3. Seasonality is defined as regular movements of demand at fixed time intervals apart. The length of the fixed time interval is known as the period of the movement. Periods of 12 months may exist for ice cream, spare ribs, strawberries, etc.

4. Cycles are usually due to long term business activity and are not addressed in this study since the predictive periods for the subsistence items are relatively short.

5. Randomness represents sporadic, short-lived movements in demand due to chance events. Randomness is reflected in the residual left after a demand series has been removed of level, trend, and seasonality.

The purpose of these statistical forecasting methods is to identify and track the level, trend, seasonal, and random components of the demand patterns. In the analyses in this report, each class of forecasting techniques is evaluated as to their appropriateness to identify and track these components.

Data requirements for statistical forecasting vary depending on the technique chosen. In this study, at least 24 lead time demand observations were used to fit the respective technique. The technique was then evaluated for accuracy over the next 24 to 40 months against the current subsistence forecast method.

Table 4 depicts the notation and data structuring used to generate and evaluate demand forecasting techniques for the subsistence commodity.

Table 4

DATA STRUCTURING FOR SUBSISTENCE DEMAND FORECASTING

Monthly
Demands

Jan 80																		Nov 83
X_{31}	X_{32}	X_{33}	...	x_{51}	X_{52}	X_{53}	...	X_{61}	X_{62}	X_{63}	...	X_{71}	X_{72}	X_{73}	X_{74}	X_{75}	X_{76}	X_{77}

Let: t = the last month of observed demand

LT = the lead time (in months) for an item

PC = the procurement cycle (in months) for an item

X_t = the observed demand in month t

$D_{t,R}$ = total demand over R months including and immediately preceding month t:

$$D_{t,R} = \sum_{i=1}^{R} X_{t+i-R}$$

Y_t = $D_{t+LT,LT}$ = the sum of the demands over the lead time following month t:

$$D_{t+LT,LT} = \sum_{i=1}^{LT} X_{t+i}$$

Z_t = $D_{t+LT+PC,PC}$ = the sum of the demands over the procurement cycle after the lead time following month t:

$$D_{t+LT+PC,PC} = \sum_{i=1}^{PC} X_{t+LT+i}$$

= the number of "lags" used in autoregressive models--the number of demands including and immediately preceding the current demand that is used in the autoregressive models

$\hat{Y}_t$ = forecast for lead time demand

$\hat{Z}_t$ = forecast for procurement cycle demand.

2. Example of Notation Used for Forecasting Techniques

An example of this notation for autoregressive techniques follows.

Let item S be a semiperishable item with a lead time of 4 months and procurement cycle of 2 months. For semiperishable items, 30 months of data were used to initially fit different forecast models.

The notation in Table 4 is applied as follows:

Monthly
Demands

$X_{25}\ X_{26}\ X_{27}\ \cdots\ x_{30}\ X_{31}\ X_{32}\ X_{32}\ X_{33}\ X_{34}\ X_{35}\ X_{36}\ X_{37}\ \cdots$

At $t = 30$, the next lead time demand for item S is $D_{30+4,4} = D_{34,4} = X_{31} + X_{32} + X_{33} + X_{34}$. At $t = 30$, the next procurement cycle demand for item S is $D_{30+4+2,2} = D_{36,2} = X_{35} + X_{36}$. In this example, a forecast will be generated for a simple autoregressive model (without constant) lagged one monthly period. The autoregressive models contain coefficients displaying the portion of past performance which affects or explains future performance. The first 30 months are used to initially fit or "prime" the forecasting models.

The simple autoregressive forecast for the next lead time demand is a_1X_{30} where a_1 is determined by the initial fitting. For example, if $a_1 = 2.62$, FORECAST$(X_{31} + X_{32} + X_{33} + X_{34}) = 2.62 * X_{30}$. Similarly, forecast for the next procurement cycle demand is b_1X_{30} where b_1 is determined by the initial fitting. If $b_1 = 1.64$, then FORECAST$(X_{35} + X_{36}) = 1.64 * X_{30}$. At month 34, the lead time FORECAST, ACTUAL AND ERROR = ACTUAL - FORECAST values are recorded. At month 36, the Procurement Cycle Forecast, Actual and Error = Actual - Forecast Values are recorded. At month 31, the procedure is repeated to develop a FORECAST$(X_{32} + X_{33} + X_{34} + X_{35})$ and a FORECAST$(X_{36} + X_{37})$. The autoregressive coefficient is updated also.

The procedure iterates until we forecast $D_{75,4}$ for lead time demand and $D_{77,2}$ for procurement cycle demand. The values recorded are altogether recorded for further analysis.

D. Forecasting Techniques

1. Discussion. In this section, a short description of the classes of forecasting techniques employed in this study is provided. More detail is available in Appendix N. The forecast techniques were selected for a variety of reasons depending on the nature of the underlying demand patterns. In particular, Autoregressive Integrated Moving Average (ARIMA) models were avoided because a monthly update of the parameter estimates is computationally expensive and difficult.

2. Description of Techniques. A short description of each class of forecasting technique is given below. Details are left to Appendix N.

a. Autoregressive Models An autoregressive (AR) model assumes that near item future demands are dependent on past and current demands. The coefficients in the autoregressive model display the fraction of the known demand affecting the future demand. In this study, the autoregressions were limited to lags of 1, 2, or 3 periods past. The study also considered logarithmic and square root auto regressive models (LAR, SAR, AR1, AR2 and AR3).

The AR3 forecasts would be as follows:

Lead Time Demand Forecast = a_1 * (last period's demand)
+ a_2 * (demand two periods ago)
+ a_3 * (demand three periods ago)
+ a_4

where the parameters, a_i, are determined by least square fits.

Procurement Cycle Demand Forecast = b_1 * (last period's demand)
+ b_2 * (demand two periods ago)
+ b_3 * (demand three periods ago)
+ b_4

where the parameters, b_i, are determined by least square fits.

We may set $a_4 = b_4 = 0$ (autoregressive without constant) or we may achieve extra freedom in the model fitting by allowing all real values for a_4 and b_4.

The inclusion of parameters a_4 and b_4 allows for tracking the average level of demand over the study period so that the autoregressive parameters can model changes in the average demand. This allows for demand series with a relatively constant change in demand to be fit by setting the autoregressive parameters equal to the periodic changes. In fact, a fractional change in demand may be modeled by the autoregressive parameters while the constant terms capture the additive component of change in demand. Some of the benefits of integrated models (to be discussed) may be achieved by these models while integrated techniques can be used to fit varying changes in demand.

b. Autoregressive Models with Harmonic Terms These models (AR1 HARM, etc.) are identical to the autoregressive models above, except for the inclusion of a harmonic term, $A \cdot \sin\left[\left(\frac{2\pi}{C} t + \theta\right)\right]$, which introduces a amplitude change and phase shift at time t to the fitting of the demand data. In this study only C = 12 for monthly demands was examined.

Note that for computational purposes:

$$A \cdot \sin\left(\frac{2\pi}{C} t + \theta\right) = a' \sin \frac{2\pi t}{C} + a \cos \frac{2\pi t}{C}$$

These models will capture consistent sinusoidal seasonal variations in demand. However, if the seasonal effects are changing from year to year and the variations are not sinusoidal, these models may introduce serious distortions.

c. Autoregressive Models with Lag Seasonal Terms. These models (AR1 LAG, etc) are identical to the autoregressive models with the exception that an additional demand period 12 months prior was included for extra freedom in the autoregressive fitting process. These models have the additional feature over simple autoregressive models of tracking varying seasonal effects that are not sinusoidal. The predictor periods and the lag periods (3, 6, 9, etc.) may be altered based on management concerns. For example, if cheese items exhibit quarterly peaks due to customer buying habits at certain times, these methods can best track the seasonal component and result in better forecasts.

d. Integrated Autoregressive Models. While autoregressive models with a constant can model certain additive trends, integrated autoregressive models (IAR) can best predict demand when the trend component changes stochastically subject to random shocks. These integrated autoregressive models are similar to autoregressive models except that the independent variable is the difference in demand between successive time periods and the dependent variable is the difference between the forecast and this period's demand. A constant may be included in the regression, if necessary.

e. Integrated Autoregressive Models with Harmonic Terms. These models (IAR HARM) are similar to the above except for the addition of the harmonic term. They may be used when the demand pattern exhibits varying trend and relatively constant sinusoidal seasonality.

f. Integrated Autoregressive Models with Lag Seasonal Terms.

These model (IAR LAG) are identical to integrated autoregressive models with the exception of an additional term which is the difference of demand over successive periods 12 months ago. (See Appendix N for the formula.) They may be used to model varying trend and "spiked" seasonal demand patterns.

Longer predictor periods can smooth out random fluctuations in the demand data. For this study, lead time/procurement cycle demand and six month sums of demands were examined.

Integrated (short-term differenced) data are used to stabilize time varying levels while logarithmic and square root transformations are included to stabilize time changing standard deviation and variance of the demand data respectively. Harmonic and lag seasonal models are included across all these classes of models.

g. Averaging Methods

Averaging methods (MO AVG) employed in this study were limited to 3, 6, 9, 12, 15, 18, 21, 24, and 36 months moving average and a arithmetic average or global mean.

The moving average methods generate the next period's forecast by averaging the actual demand over a certain period. These methods are intended to cancel out random fluctuations in demand. The methods do not accommodate seasonality. A wide range of periods was studied to determine the proper length of period.

Too few periods will result in seriously distorted forecasts influenced by random variations in demand. Too many periods will result in lagging forecasts which fail to track trends. When the level of the demand does change, the proper moving average will respond well unlike the last period demand forecast which will fail to adjust at all.

The arithmetic average or global mean is the arithmetic average of all actual demand values from the start to the end of the evaluation period.

The arithmetic average will smooth out random fluctuations, but for long evaluation periods, it does not respond well to trends nor seasonality. It takes little account of recent data. It is appropriate for randomly distributed data with a constant level.

h. Naive Methods. Managers often look to the last period's data or this period's data one year ago before making decisions concerning stock buys and levels. In this report, these techniques are denoted as:

(1) Last Period's Observation. For this method, actual demand is the forecast for the predictor period. The last period's observation may work well with data that exhibit local monotonic trends, but it does not accommodate seasonality and may "chase" random fluctuation resulting in poor forecasts.

(2) This Period Last Year. This technique (LAST YEAR) merely uses the demand recorded for the predictor period one year ago as the predictive period forecast. This method ignores recent observations and therefore fails to track trends. The method is appropriate for demands with an annual seasonal pattern and constant level; however, it can overreact to random fluctuations.

i. Exponential Smoothing (Exponentially Weighted Moving Average). Exponential smoothing techniques are widely used in Government and industry due to their ease of computation and minimal data retention requirements. Single exponential smoothing (SES) and double exponential smoothing (DES) are more commonly used.

The choice of a smoothing constant is critical to the performance of the exponential smoothing methods. The order of exponential smoothing is usually decided by visual inspection of the data. For demand series with slowly changing levels, single exponential smoothing is selected. For demands that grow or decay linearly over time, double exponential smoothing is chosen. Smoothing constants between .05 and .30 are usually suggested. However, in this study, smoothing constants of .4, .5, .6, .7, .8, and .9 were also tested.

There are many methods to adjust exponential smoothing for seasonal patterns. One such famous method is known as Winter's seasonal forecast procedure. Winter's procedure incorporates three smoothing constants; one to update the level, one for trend, and one for seasonality. Because of the effort required to estimate the proper smoothing parameters, the Winter's method was not included in this study.

Extreme care must be taken when describing the formulae and computer code for double exponential smoothing.* Many erroneous formulae have, in fact, been published and caution is warranted when dealing with the subject. The correct formula for the one period ahead forecast under double exponential smoothing is:

$$(2S^1 - S^2) + \frac{\alpha}{1-\alpha}(S^1 - S^2)$$

where S^1 is the single smoothed average, S^2 is the double smoothed average and α is the smoothing constant.

* See Reference 3; Gardner, E. S., "The Strange Case of the Lagging Forecast," Interfaces, May-June 1984.

As used by DLA, the subsistence semiperishable forecast calculates the double smoothed one period ahead forecast correctly, but then simply multiplies the monthly forecast by the lead time period. Trends are assumed constant over the lead time.

The exponential smoothing parameters, α, in the single and double exponential smoothing formulae above, are constant.

Another technique known as Adaptive Response Rate Single Exponential Smoothing (ARRS(γ)) allows for the controlled change of the smoothing parameter. At each period, the absolute value of the single smoothed average error and the single smoothed average absolute error through the last period is calculated. The new smoothing constant is chosen as the minimum of this ratio and γ. The constraint method was needed due to wild forecast fluctuations when the smoothing was unconstrained. COMBINED exponential smoothing is discussed in Section IIIE.

3. Model Identification. Figure 2 provides a schematic of the data structuring and forecast model development used in this study. The first task of Model Identification involved fitting the various autoregressive forecasting schemes to the demand data. First, using a set number of points to prime the models; second, to generate a single predictive period forecast; and third, to recursively add points, refit the regression and generate lead time and procurement cycle forecasts until actual demand periods are exhausted. The Model Identification phase involved processing approximately 7,850 series of subsistence demand history through over 100 autoregressive type models as described in Section III and Appendix N. A typical iterative autoregression report is provided in Table 5.

Table 5 depicts the fitting of an integrated autoregressive harmonic model to the demand series for Pork Spareribs stocked at Bremerhaven, Germany. The predictor period is six months, i.e., six month sums of demand are used to estimate the lead time and procurement cycle demand.

The key statistics in Table 5 are given in the RESULTS area at the bottom of the report. It is important to note that the Mean Absolute Deviation (MAD) and the Mean Absolute Percentage Error (MAPE) are generally considerably less for the subject model (IFCT) than the present DLA model (DFCT). The MAD and MAPE are measures of forecast accuracy. Appendix B provides a detailed description of the terms in the autoregression report.

The fact that the subject model, which is seasonal, has been more accurate in forecasting this item's demand would indicate that the demand pattern may be seasonal. It must be considered that six parameters were required to generate this model. A simpler model may identify the seasonal pattern and perform just as well.

After developing the report in Table 5, the nomenclature and other item data, the actual lead time and procurement cycle demand, and the forecast errors from the autoregressive models are stored for further analysis.

In summary, Table 5 provides a report for comparing various autoregressive forecasting models against the present DLA method. Various statistical measures of forecast accuracy such as mean absolute deviation, mean error, and mean absolute percentage error are given to assist the analyst in reviewing various autoregressive models.

FIGURE 2

SCHEMATIC OF DATA STRUCTURING
AND FORECAST MODEL DEVELOPMENT

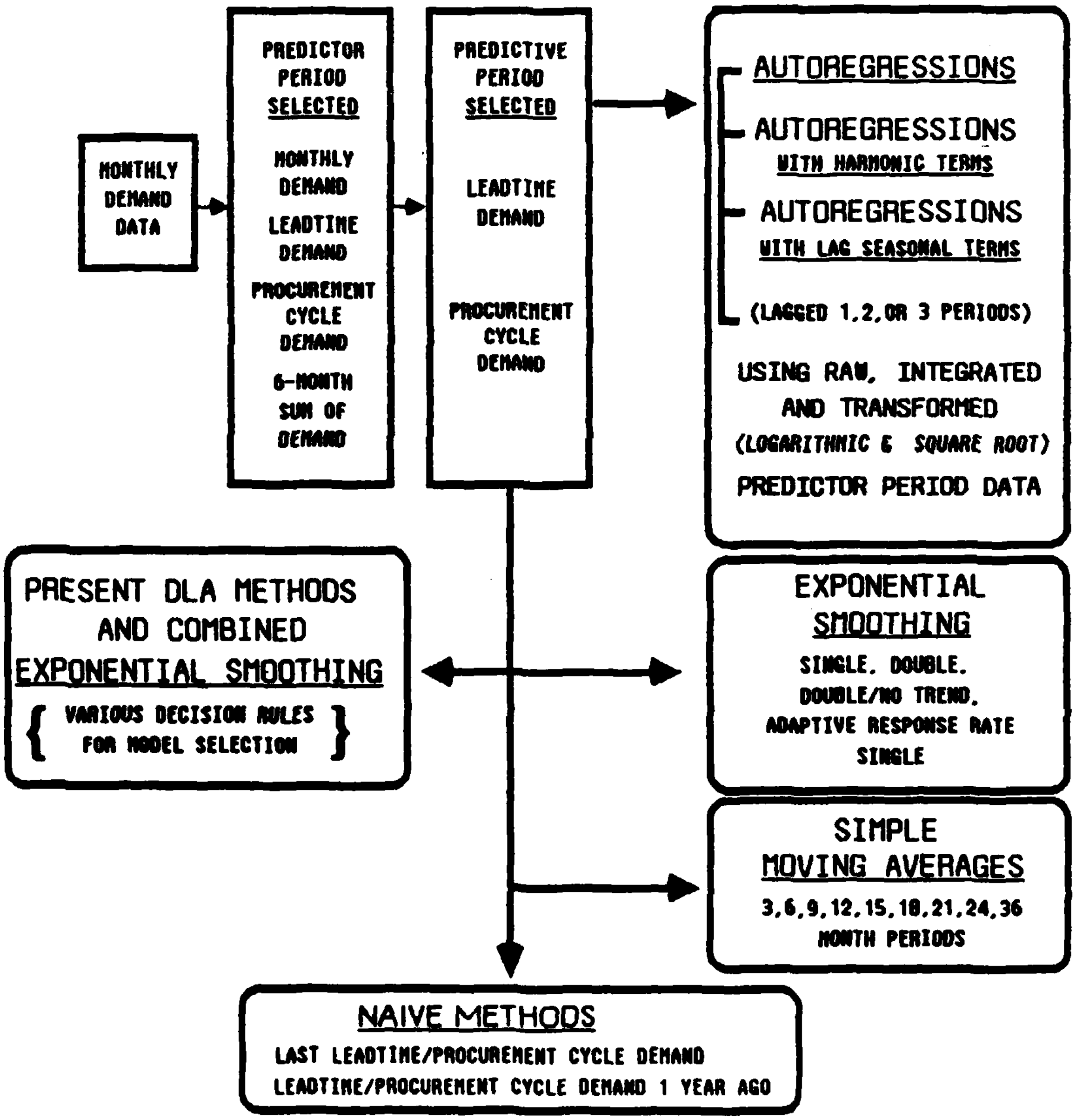


Table 5

SAMPLE AUTOREGRESSION REPORT

```
PERISHABLES          --  INTEGRATED 6-MO AR3 HARMONIC WITH CONSTANT          MODEL =        24
   NSN        PCK DEP  LT   PC  NOMENCLATURE                        NDP      ITEM #
8905001268743  1  LB    3    1  PORK, SPARERIBS, FROZEN              71       1397
```

MONTH	LEAD TIME ESTIMATES ACT	IFCT	ERR	% ERR	DFCT	ERR	% ERR	MONTH	PROCUREMENT CYCLE ESTIMATES ACT	IFCT	ERR	% ERR	DFCT	ERR	% ERR
36:	226438	204500	21938	.10	206897	19541	.09	36:	66133	53918	12215	.18	68966	-2833	-.04
37:	204984	191038	13946	.07	240344	-35360	-.17	37:	54132	69969	-15837	-.29	80115	-25983	-.48
38:	182799	196577	-13778	-.08	231189	-48390	-.26	38:	41677	68802	-27125	-.65	77063	-35386	-.85
39:	161942	222118	-60176	-.37	207020	-45078	-.28	39:	58331	53405	4926	.08	69007	-10676	-.18
40:	154140	207975	-53835	-.35	201692	-47552	-.31	40:	46678	50538	-3860	-.08	67231	-20553	-.44
41:	146686	173824	-27138	-.19	172598	-25912	-.18	41:	46250	38779	7471	.16	57533	-11283	-.24
42:	151259	149625	1634	.01	143486	7773	.05	42:	59376	52474	6902	.12	47829	11547	.19
43:	152304	165209	-12905	-.08	164567	-12263	-.08	43:	59744	81677	-21933	-.37	54856	4888	.08
44:	165370	191141	-25771	-.16	143360	22010	.13	44:	64263	71422	-7159	-.11	47787	16476	.26
45:	183383	210509	-27126	-.15	145004	38379	.21	45:	82558	66506	16052	.19	48335	34223	.41
46:	206565	213554	-6989	-.03	165216	41349	.20	46:	75146	71335	3811	.05	55072	20074	.27
47:	221967	212656	9311	.04	172301	49666	.22	47:	80557	60202	20355	.25	57434	23123	.29
48:	238261	205087	33174	.14	188086	50175	.21	48:	36142	48514	-12372	-.34	62695	-26553	-.73
49:	191845	196977	-5132	-.03	227120	-35275	-.18	49:	32087	59903	-27816	-.87	75707	-43620	-1.36
50:	148786	180791	-32005	-.22	223703	-74917	-.50	50:	41005	46998	-5993	-.15	74568	-33563	-.82
51:	109234	169172	-59938	-.55	239966	-130732	-1.20	51:	38505	47443	-8938	-.23	79989	-41484	-1.08
52:	111597	125674	-14077	-.13	150135	-38538	-.35	52:	52460	35768	16692	.32	50045	2415	.05
53:	131970	115181	16789	.13	122523	9447	.07	53:	49619	41505	8114	.16	40841	8778	.18
54:	140584	115284	25300	.18	116124	24460	.17	54:	53257	44305	8952	.17	38708	14549	.27
55:	155336	141129	14207	.09	113556	41780	.27	55:	73837	63836	10001	.14	37852	35985	.49
56:	176713	181454	-4741	-.03	144675	32038	.18	56:	66692	74495	-7803	-.12	48225	18467	.28
57:	193786	216376	-22590	-.12	144720	49066	.25	57:	68184	75039	-6855	-.10	48240	19944	.29
58:	208713	208266	447	.00	157553	51160	.25	58:	57585	52975	4610	.08	52518	5067	.09
59:	192461	182064	10397	.05	199112	-6651	-.03	59:	56003	50232	5771	.10	66371	-10368	-.19
60:	181772	155570	26202	.14	196931	-15159	-.08	60:	50730	57244	-6514	-.13	65644	-14914	-.29
61:	164318	160603	3715	.02	206633	-42315	-.26	61:	44105	50596	-6491	-.15	68878	-24773	-.56
62:	150838	154687	-3849	-.03	182608	-31770	-.21	62:	30490	41576	-11086	-.36	60869	-30379	-1.00
63:	125325	141645	-16320	-.13	174890	-49565	-.40	63:	35635	35545	90	.00	58297	-22662	-.64
64:	110230	124134	-13904	-.13	158254	-48024	-.44	64:	42078	32800	9278	.22	52751	-10673	-.25
65:	108203	122500	-14297	-.13	141576	-33373	-.31	65:	49506	50715	-1209	-.02	47192	2314	.05
66:	127219	129093	-1874	-.01	108398	18821	.15	66:	48760	48280	480	.01	36133	12627	.26
67:	140344	144743	-4399	-.03	108567	31777	.23	67:	42259	55552	-13293	-.31	36189	6070	.14
68:	140525	150068	-9543	-.07	117218	23307	.17	68:	41008	59136	-18128	-.44	39073	1935	.05
69:	132027	168005	-35978	-.27	137868	-5841	-.04	69:	48573	65227	-16654	-.34	45956	2617	.05
70:	131840	179872	-48032	-.36	143312	-11472	-.09	70:	46010	62245	-16235	-.35	47771	-1761	-.04
71:	135591	184094	-48503	-.36	133651	1940	.01	71:	29848	48892	-19044	-.64	44550	-14702	-.49
72:	124431	166873	-42442	-.34	127526	-3095	-.02	72:	33102	30339	2763	.08	42509	-9407	-.28
73:	108960	144634	-35674	-.33	138779	-29819	-.27	73:	50272	26617	23655	.47	46260	4012	.08

RESULTS	MAD	MERR	MAPE	MAD	MERR	MAPE	MAD	MERR	MAPE	MAD	MERR	MAPE
	21528	-12209	.15	33784	-6800	.22	10960	-2426	.23	16755	-3854	.36

```
NO OF FIT PARAMETERS =  6
 LEAD TIME PARAMETERS :     -.72    -1.01    -.74  23264.16  41052.29  -9041.75
 PROC CYCLE PARAMETERS :     .27      .05    -.58 -19487.57   9958.97  -2671.50
```

The next part of Model Identification involves the additional selection of exponential smoothing, moving average, and naive methods to the autoregressive methods. The user may select any combination of these desired. In this study, a wide range of moving averages, exponential smoothing models for different smoothing parameters, and two naive models were investigated. Model evaluation then begins.

E. Evaluation Criteria

One goal of a forecasting system is the minimization of the total forecast error incurred over time. Traditionally, squared forecast errors have been a useful measure of accuracy with Mean Squared Error (MSE) recognized as a popular choice.

MSE is defined as follows:

$$MSE = \frac{1}{n} \sum_{t=1}^{m} (A_t - F_t)^2$$

where: A_t is the actual demand and F_t is the forecasted demand.

MSE is closely related to variance and is widely accepted in statistics as a measure of being close. Root Mean Squared Error (RMSE) is the square root of MSE and is closely related to standard deviation.

The squared error measures have the advantage of penalizing large forecast errors and ignoring the sign of the error. One drawback of squared error measures is determining the level of significance between two models. For example, what is the significance of accuracy between an RMSE of 25 and 30? This limitation notwithstanding, the ratio of the RMSE of a test model versus the RMSE of the current DLA method and the standard deviation of this ratio are included as evaluation criteria for model selection. Table 6 is a sample model test set evaluation report. In it, the models are ranked by RMSE and the ratio of the RMSE for the test model and the RMSE for the no-change model (LAST LT/PC). A complete description of the model evaluation report is provided in Appendix E.

There are economic benefits to be gained by demand variance reduction. In DoD inventory models, the total variable cost is the sum of ordering, holding, and stockout costs. A Subsistence Inventory Simulation is not presently available to test the performance of different forecasting models in terms of total inventory costs. However, it has been documented that a particular forecasting model's accuracy (as measured by Mean Squared Error) plays a vital role in keeping total stockout costs reasonable and that holding costs can be reduced by study of the sources of lead time demand variance (Reference 14).

Other evaluation criteria, used in this study, relate to the Theil decomposition of the forecast error into bias, regression, and disturbance proportions. Bias distorts forecast accuracy through systematic overforecasting or underforecasting. When Theil's bias proportion exceeds .2, the model is rejected for selection. For a complete description and application of the Theil decomposition, the reader should review References 15 and 16, respectively.

Table 6

SAMPLE FORECAST MODEL EVALUATION REPORT

```
          --- PORK, SPARERIBS, FROZEN                   LEADTIME
           NSN: 8905001268743   ITEM NO: 00520   LEADTIME:  3   PROC CYCLE:  1   RIC/DEPOT :LB
CHILL CODE: 2   SHELF LIFE: 06   VSL: 4 UI: LB   NET WGT: 000052   SUPPLY CODE:     ISSUE CODE:     FLEET CODE: 0
-------------------------------------------------------------------------------------------------------------------
MEAN: 176908 STDEV:  38548  MAD:  34201  MEDIAN: 185591  T-MEAN 177343  MAD/SD:   .89 C/VAR:  .22 C/SKEW:  -.09  C/EXC: -1.20
-------------------------------------------------------------------------------------------------------------------
                    TREND  47.3 (DF:  4  F: 29.1)  SEAS  34.8 (DF: 11  F:  7.8)  RAND  17.9 (DF: 44)

                     SEAS: 103.7  85.9  81.0  81.9  88.9  95.0 101.1 107.7 115.7 117.7 117.3 104.2
                    TREND: 112.8 115.4 104.5  92.8  74.4

              % POS CHANGES: 49.3 48.5 47.7 48.4 46.0 41.9 41.0 40.0 35.6 36.2 28.1 30.4
                    % TURNS: 28.4 22.7 16.9 17.2 17.5 17.7 18.0 16.7 15.3 17.2 21.1 25.0
-------------------------------------------------------------------------------------------------------------------
                       MEAN   STDEV         1  2  3  4  5  6  7  8  9 10 11 12 CHI-SQ
      RAW DATA       176908   38548         +  +  +  .  .  .  .  .  .  +  +  + 124.2 AUTO
                                            +  -  .  .  .  .  +  .  .  .  .  .  77.8 PART
                                            .  .  .  .  -  .  +  +  +  .  .  .  66.2 LAG
      RAW INT          -669   20343         +  .  -  .  .  -  .  .  .  .  .  .  73.7
      CROSS CORR                            +  +  .  .  .  .  .  .  +  +  +  +  78.5
    * CROSS INTEG                           .  .  .  .  .  .  .  .  .  .  .  .  20.5
-------------------------------------------------------------------------------------------------------------------
                       MEAN    RMSE  THEIL                                             BIAS  REGR  DIST  OLC RMSE  OLC THEIL
      INAR3C HARM     -9585   24629    .56  +  .  .  .  .  .  .  .  .  .  .  .   49.2   .15   .02   .82    22324       .51
      INAR2C HARM     -8403   25253    .58  +  .  .  .  .  .  .  .  .  .  .  .   54.0   .11   .05   .83    23042       .53
      INAR1C HARM     -8222   27060    .62  +  .  .  -  .  .  .  .  .  .  .  .   44.2   .09   .14   .77    23689       .54
      LAST YEAR      -21656   32951    .75  +  .  .  .  .  .  .  .  .  .  .  .   31.4   .44   .03   .53    23950       .55
      NAR3C HARM     -22469   33214    .76  +  .  .  .  .  .  .  .  .  .  .  .   33.3   .46   .00   .54    24317       .56
      NAR1C LAG      -20087   33316    .76  +  .  .  .  .  .  .  .  .  .  .  .   42.6   .37   .00   .63    26456       .60
      12-MO AVG      -12552   33706    .77  +  .  .  .  -  -  .  .  .  .  .  .  116.2   .14   .01   .85    31059       .71
      NAR2C HARM     -26156   34335    .78  +  .  .  .  .  .  .  .  .  .  .  .   32.1   .59   .00   .41    22025       .50
      NAR1C HARM     -27914   34520    .79  +  .  .  .  .  .  .  .  .  .  .  .   31.5   .66   .01   .33    19933       .46
      NAR2C LAG      -22348   35190    .80  +  .  .  .  .  .  .  .  .  .  .  .   33.9   .41   .00   .59    27044       .62
      NAR3C LAG      -22851   36481    .83  +  .  .  .  .  .  .  .  .  .  .  .   34.7   .40   .00   .60    28242       .64
      18-MO AVG      -14834   38883    .89  +  .  .  .  -  -  .  .  .  .  .  .  130.8   .15   .01   .84    35572       .81
      DLA             -5522   40339    .92  +  .  .  -  -  -  .  .  .  .  .  .   93.4   .02   .29   .69    33594       .77
      INAR3C          -2539   41964    .96  +  .  .  .  .  -  .  .  .  .  .  .   69.6   .00   .26   .73    35946       .82
      NAR2C          -30298   42587    .97  +  .  .  .  .  .  .  .  .  .  .  .   35.8   .51   .02   .47    29226       .67
      INAR2C          -2098   42704    .98  +  .  .  .  -  -  .  .  .  .  .  .  118.7   .00   .29   .70    35844       .82
      NAR3C          -32240   43220    .99  +  .  .  .  .  .  .  .  .  .  .  .   30.2   .56   .01   .43    28216       .64
      LAST LT/PC      -6230   43792   1.00  +  .  .  -  -  -  .  .  .  .  .  .  126.2   .02   .32   .66    35581       .81
      NAR1C          -26192   44098   1.01  +  .  .  .  -  -  .  .  .  .  .  .  107.5   .36   .00   .64    35202       .80
      INAR1C          -1987   44498   1.02  +  .  .  -  -  -  .  .  .  .  .  .  120.3   .00   .37   .63    35398       .81
      GLOBAL MN      -27424   44747   1.02  +  +  .  .  .  .  .  .  .  .  .  .   86.1   .38   .06   .56    33379       .76
      6-MO AVG        -6895   46553   1.06  +  .  .  .  -  -  .  .  .  .  .  .  156.3   .02   .32   .66    37733       .86
      INAR3C LAG     -19319   54618   1.25  +  .  .  .  .  .  .  .  .  .  .  .   31.6   .13   .55   .32    30878       .71
      INAR2C LAG     -21343   60108   1.37  +  .  .  .  .  .  .  .  .  .  .  .   34.4   .13   .61   .26    30633       .70
      INAR1C LAG     -21808   65630   1.50  +  .  .  .  .  .  .  .  .  .  .  .   31.3   .11   .67   .22    30583       .70
```

Table 6

(continued)

```
     --- PORK, SPARERIBS, FROZEN           PROCUREMENT CYCLE
      NSN: 8905001268743   ITEM NO: 00520  LEADTIME:  3   PROC CYCLE:  1   RIC/DEPOT :LB
CHILL CODE: 2   SHELF LIFE: 06   VSL: 4 UI: LB   NET WGT: 000052   SUPPLY CODE:     ISSUE CODE:      FLEET CODE: 0
------------------------------------------------------------------------------------------------------------------
MEAN:  58305 STDEV:  15532  MAD:  13122  MEDIAN:  59139  T-MEAN  58212  MAD/SD:   .84 C/VAR:   .27 C/SKEW:  -.04  C/EXC:  -.86
------------------------------------------------------------------------------------------------------------------
                 TREND  32.3 (DF:  4  F: 10.9)  SEAS  35.2 (DF: 11  F:  4.3)  RAND  32.6 (DF: 44)

                  SEAS:  70.9  86.3  92.1  92.2 104.6 110.9 112.2 129.0 117.1 110.7  89.3  84.7
                 TREND: 114.4 115.3 100.7  98.2  73.4

                 % POS CHANGES: 47.8 50.0 47.7 46.9 49.2 43.5 36.1 33.3 37.3 36.2 35.1 33.9
                       % TURNS: 56.7 27.3 30.8 21.9 22.2 19.4 18.0 18.3 22.0 19.0 33.3 37.5
------------------------------------------------------------------------------------------------------------------
                    MEAN   STDEV        1  2  3  4  5  6  7  8  9 10 11 12 CHI-SQ
     RAW DATA      58305   15532        +  +  .  .  .  .  .  .  .  +  +  +  78.7 AUTO
                                        +  .  .  .  .  .  .  +  +  .  .  .  42.4 PART
                                        .  .  .  .  .  .  .  .  +  .  .  .  18.7 LAG
   * RAW INT        -598   13934        .  .  .  .  .  .  .  .  .  .  .  .  11.7
     CROSS CORR                         .  .  .  .  .  +  +  +  +  +  +  .  56.0
     CROSS INTEG                        .  .  .  -  .  .  .  .  +  .  +  .  34.1
------------------------------------------------------------------------------------------------------------------
                    MEAN    RMSE  THEIL                                            BIAS  REGR  DIST   OLC RMSE   OLC THEIL
     12-MO AVG     -5470   14320   .69  +  .  .  .  -  -  .  .  .  .  .  .  59.9   .15   .00   .85    13188       .63
     NAR1C LAG     -8422   15329   .73  +  .  .  .  .  .  .  .  .  .  .  .  28.3   .31   .00   .69    12759       .61
   * LAST YEAR     -7297   15369   .74  .  .  .  .  .  .  .  .  .  .  .  .  11.9   .23   .16   .61    12036       .58
     NAR2C LAG     -9836   15806   .76  +  .  .  .  .  .  .  .  .  .  .  .  25.3   .39   .03   .58    12027       .58
     18-MO AVG     -6230   16014   .77  +  .  .  .  -  -  .  .  .  .  .  .  77.5   .15   .03   .82    14500       .69
     INAR3C HARM   -5224   16585   .79  +  .  .  .  .  .  .  .  .  .  .  .  59.0   .10   .20   .70    13827       .66
     NAR3C LAG    -10823   16885   .81  +  .  .  .  .  .  .  .  .  +  .  .  35.2   .42   .04   .55    12476       .60
     INAR2C HARM   -5227   17438   .83  +  .  .  .  .  .  .  .  .  .  .  .  54.3   .09   .26   .65    14046       .67
     GLOBAL MN    -10427   17689   .85  +  .  .  .  .  .  .  .  .  .  .  .  52.4   .35   .03   .62    13896       .67
     NAR3C HARM    -8865   17721   .85  +  .  .  .  -  .  .  .  .  .  .  .  63.7   .25   .13   .62    13910       .67
     INAR1C HARM   -4422   17962   .86  +  .  .  .  .  -  .  .  .  .  .  .  56.2   .06   .30   .64    14316       .69
     NAR2C        -13665   18098   .87  +  .  .  .  .  .  .  .  .  .  .  .  23.2   .58   .03   .39    11319       .54
     NAR1C        -12690   18217   .87  +  .  .  .  .  .  .  .  .  .  .  .  23.0   .49   .07   .44    12092       .58
     NAR2C HARM   -10066   18496   .89  +  .  .  .  -  .  .  .  .  .  .  .  66.3   .30   .11   .59    14198       .68
     6-MO AVG      -3584   18589   .89  +  .  .  .  -  -  .  .  .  .  .  . 115.9   .04   .32   .64    14849       .71
     INAR3C        -2149   18890   .90  +  .  .  .  -  -  -  .  .  .  .  . 113.3   .01   .37   .62    14829       .71
     NAR1C HARM   -11703   19081   .91  +  .  .  .  .  .  .  .  .  .  .  .  62.8   .38   .08   .53    13946       .67
     NAR3C        -15097   19576   .94  +  .  .  .  .  .  .  .  .  .  .  .  24.5   .60   .00   .40    12366       .59
     DLA           -3126   20181   .97  +  .  .  -  -  -  .  .  .  .  .  . 117.1   .02   .43   .54    14877       .71
     LAST LT/PC    -2890   20892  1.00  +  .  .  -  -  -  .  .  .  .  .  .  93.9   .02   .47   .51    14876       .71
     INAR2C        -2527   21102  1.01  +  .  .  .  -  -  -  .  .  .  .  . 119.5   .01   .50   .49    14775       .71
     INAR3C LAG    -9117   21110  1.01  +  .  .  .  .  .  .  .  .  .  .  .  15.7   .19   .44   .37    12921       .62
     INAR1C        -2641   22480  1.08  +  .  .  .  -  -  -  .  .  .  .  . 117.5   .01   .56   .42    14612       .70
     INAR2C LAG    -9620   22660  1.08  +  .  .  .  .  .  .  .  .  .  .  .  16.6   .18   .47   .34    13309       .64
     INAR1C LAG    -9466   23776  1.14  +  .  .  .  .  .  .  .  .  .  .  .  17.7   .16   .51   .33    13668       .65
```

During the evaluation phase, extensive testing was performed on the present DLA use of exponential smoothing for semiperishable subsistence. The present formula uses smoothing constants of .1, .15, and .2 (.2 only for brand name items) and simply extends the one period ahead double exponential smoothed forecast through the lead time and procurement cycle.

The decision rule to switch the smoothing constant is made on the forecast formula which has the least smoothed mean absolute deviation through the last month. The current DLA formulation, on the average, outperformed true double exponential smoothing for semiperishable subsistence; however, it was consistently less effective than single exponential smoothing.

These findings led to the testing of various decision rules for selecting the smoothing constant and the kind of exponential smoothing (single, DLA formulation, and double). A combined exponential smoothing model was designed originally as a conglomerate of 18 exponential smoothing models (single, DLA formulation, and double) for smoothing constants .05, .1, .15, .2, .25, and .30.

The following decision rules on switching models within the COMBINED model were tested:

1. Select on least smoothed MAD over the last lead time or procurement cycle, respectively, with a smoothing constant of .1.

2. Select on least smoothed MAD over the last lead time or procurement cycle, respectively, with the smoothing constant presently in use.

3. Select on least smoothed squared error over the last lead time or procurement cycle, with a smoothing constant of .1.

4. Select on least smoothed squared error of the last lead time or procurement cycle, respectively, with the smoothing constant presently in use.

Model assignment analyses (described in next section) were then made on a sample of 800 series. Decision rules 1 and 3 were found to be superior to 2 and 4 in terms of reduced RMSE and compactness distribution. Decision rule 1 was slightly better than rule 3 in terms of reduced RMSE and the number of series with a positive improvement.

Analyses were then performed on the smoothing constant to test if changing the constant for smoothing the MAD would improve forecast accuracy for decision rule 1. Model assignment analyses were performed for smoothing constants of .05, .1, and .2. The smoothing constant of .2 performed slightly better than the others in terms of reduced RMSE and number of series with a positive improvement.

Smoothing the MAD with a constant uses the same set of weights for the errors of any of the models. When an α of .2 is employed, 74 percent $(1-(.8)^6)$ of the weights used in the smoothed MAD is given to the last six errors while 93 percent $(1-(.8)^{12})$ is given to the last 12 errors.

The combined exponential smoothing method throughout this report will be denoted as COMBINED.

The original COMBINED model performed better than any other individual model when assigned to semiperishable subsistence demand series. However, it was rather cumbersome. Further testing indicated that the range of exponential smoothing formulations and smoothing constants could be narrowed down without appreciable deterioration in forecast accuracy for the COMBINED model. When the COMBINED model was limited to the single and DLA formulations for exponential smoothing with smoothing constants of .1, .2, and .3, a deterioration of only .7 percent in average RMSE was realized.

This results in a reduction of data storage requirements from 36 to 12 values per item/warehouse record for this model.

The model evaluation phase provided a means to rank the various forecast models according to statistical accuracy. At the completion of the model evaluation phase there was enough information available to begin to study the problem of assigning forecast models to classes of subsistence items.

F. Model Assignment Analysis

1. Demonstration of the Model Assignment Analysis Technique

This section of the report describes how forecast model assignments to item classes were designed and tested. Model assignment includes the study of the performance of any one over a hundred individual models to the more difficult problem of the interaction of competing models in a group. For example, if two models perform the same on most items, it is probably feasible to assign one. However, if two models perform well on distinctly different items, their performance as a group will be considerably enhanced.

All model assignment analysis performance statistics are relative to a base model. In the model assignment analyses in this report, the base model was chosen as the current DLA method. For demonstration purposes, the model assignment analysis for perishable subsistence is described here. The model assignment analysis for semiperishable subsistence is provided in Appendix D.

The final model assignment analysis report for perishable subsistence is provided for demonstration purposes. The model assignment report contains nine tables which are used to construct and test groups of forecast models for the subsistence commodity.

Table 7 provides the input specifications for the model assignment analysis. Information following the @ indicates the identification of the test under study. FORECAST file indicates the Fortran device assigned for the input file from the Model Evaluation Phase. Model TITLES file indicates the Fortran device assigned for the Model Titles. Select is an option to sort on brand name, troop issue, or not. Post-forecast Theil adjustment is an option selected to estimate magnitude of improvement when unsatisfactory models are corrected for bias and regression errors. Random residual check may be used to constrain model assignment. The Base Model is the present DLA forecast formulation or whatever other model the user may choose. The performance in the test set of all model assignments will be made relevant to the base model's performance. The CHI-Square Limitation may be used to provide a certain confidence level for randomness in the residuals.

Table 7

MODEL ASSIGNMENT ANALYSIS - PERISHABLE SUBSISTENCE:
INPUT SPECIFICATIONS

```
ANALYSIS INPUT DATA

                    *TRACKING BASED ON MAD SMOOTHED WITH CONSTANT ALPHA OF .2
                    *PERISHABLE SUBSISTENCE
                    *FINAL MODEL GROUP
 FORECAST FILE:  7
 MODEL TITLES FILE: 11
 SELECT: ALL
 POST-FORECAST THEIL ADJUSTMENT: NONE
 RANDOM RESIDUAL CHECK: NO
 BASE MODEL (20): DLA
 CHI-SQUARE LIMITATION: NONE

 MODELS ON FILE:     1: GLOBAL MEAN   2: 12-MO AVG     3: 24-MO AVG     4: 36-MO AVG     5: SES(.05)
                     6: SES(.10)      7: SES(.15)      8: SES(.20)      9: SES(.25)     10: SES(.30)
                    11: DES(.10)     12: DES(.20)     13: DES(.30)     14: ARRS(.10)    15: ARRS(.20)
                    16: ARRS(.30)    17: COMBINED     18: LAST LT/PC   19: LAST YEAR    20: DLA
                    21: AR1 LAG      22: NAR1 LAG     23: LAR1 LAG     24: LNAR1 LAG    25: SAR1 LAG
                    26: SNAR1 LAG

ANALYZED MODELS:     2: 12-MO AVG     7: SES(.15)     18: LAST LT/PC   19: LAST YEAR    21: AR1 LAG
```

The MODELS ON FILE are those generated from the identification and evaluation phase. See Appendix N for formulas and acronyms. The Analyzed models are the set which are selected to be assigned across the class of items under study resulting in an improvement or degradation in performance over the base model.

Table 8 demonstrates the assignment occurrence and individual assignment distribution matrices. For this class of items (perishable), and the predictive period (lead time) under study, the assignment occurrence table provides the frequency of occurrence of the best and second best model in terms of RMSE reduction. Models asterisked are those assigned in the analysis.

For example, the unanalyzed model 3 - (24-MO AVG) was better 240 times than the assigned model 7 - (SES(.15)) when model 7 was selected best (823 times).

The Prefer row indicates how often each unanalyzed model would be preferred to any of the assigned models. This is the sum of the columns of the occurrence matrix.

The Accept row indicates how frequently the assigned models were first or second, (e.g., 2 times the number of series being tested). The assign row indicates the best assignment among the analyzed models.

The average standard deviation index is the sum over the item class of the ratio of assigned model RMSE to base model RMSE. The number of series in the item class is also noted. The individual distribution table provides the performance distribution in deciles from -100 to 100 for each model on the file when individually assigned to the entire class of items under study. Performance is defined as the average percentage reduction in RMSE as compared to the base model. For the example, the RMSE of model 3 (24-month average) was 40 to 50% less than RMSE of the base model four times for the 1993 series under study. At the same time, the RMSE of model 3 was 40 to 50 percent greater than the RMSE of the base model 17 times.

The first matrix on Table 9 shows the performance measured by lower average ratios of assigned model RMSE to base model RMSE of individual vs. base model when each model is individually assigned across the entire class of items. The second row of this matrix indicates the standard deviation about the mean of the individual performances. The third row of this matrix provides the number of standard deviations around 100 percent wherein the mean performance lies, e.g., $\left(\frac{100 - PERF}{STD} \right)$. The second matrix of Table 9 depicts the percentage in base RMSE performance distribution in deciles from -100 to 100 and the reduction in Base RMSE for assigned model to the subclass where they are assigned. For example, for the 796 times the 12-MO average model was assigned an average reduction of 22 percent in RMSE was achieved over the base model for those 796 demand series.

Table 10 provides the assignment contribution matrix which is critical to the testing of the assigned group of models. The assignment contribution matrix is a tool which can be used to show whether additional performance may be gained by adding or switching models.

In the study of the assignment contribution it is important to remember the distinction between the assigned and unanalyzed models on the file.

Table 8

MODEL ASSIGNMENT ANALYSIS - PERISHABLE SUBSISTENCE: LEAD TIME DEMAND - ASSIGNMENT OCCURRENCE AND INDIVIDUAL ASSIGNMENT DISTRIBUTION MATRICES

TROOP ISSUE AND BRAND NAME

LEADTIME	1	2 *	3	4	5	6	7 *	8	9	10	11	12	13	14	15	16	17	18 *	19 *	20	21 *	22	23	24	25	26
2*	206	796	238	200	206	179	715	46	40	34	31	5	0	53	16	4	96	2	35	4	44	20	7	16	13	18
7*	270	684	240	246	275	392	823	323	272	233	81	23	3	104	84	46	265	115	0	33	24	14	5	21	9	20
18*	8	11	2	4	13	6	122	36	70	89	23	29	1	21	55	49	57	168	0	76	35	5	5	11	8	8
19*	2	27	8	3	1	0	2	0	0	0	0	0	0	0	0	0	0	0	72	0	43	3	3	5	5	7
21*	13	44	12	12	9	4	34	5	6	8	6	3	2	7	4	3	10	21	35	14	134	27	32	30	64	36
PREFER	499	0	500	465	504	581	0	410	388	364	141	60	6	185	159	102	428	0	0	127	0	69	52	83	99	89
ACCEPT	0	1562	0	0	0	0	1696	0	0	0	0	0	0	0	0	0	0	306	142	0	280	0	0	0	0	0
ASSIGN	0	796	0	0	0	0	823	0	0	0	0	0	0	0	0	0	0	168	72	0	134	0	0	0	0	0

AVERAGE STD DEV INDEX (BASE MODEL 20): 83.2 1993 SERIES ACCEPTED

REDUCTION IN BASE RMSE

MODEL	100	90	80	70	60	50	40	30	20	10	0	-10	-20	-30	-40	-50	-60	-70	-80	-90	-100
1:	0	0	0	0	1	7	133	338	449	347	225	139	95	57	51	30	21	16	18	66	
2:	0	0	0	0	0	4	142	508	608	404	151	87	43	23	13	7	0	1	0	2	
3:	0	0	0	0	1	4	160	415	540	351	225	106	78	35	17	19	13	7	5	17	
4:	0	0	0	0	0	8	131	388	457	369	209	151	77	62	36	24	12	9	13	47	
5:	0	0	0	0	1	5	133	386	510	381	203	130	68	49	35	23	13	12	6	38	
6:	0	0	0	0	0	2	118	512	665	387	164	66	30	24	8	6	6	1	2	2	
7:	0	0	0	0	0	1	74	522	768	399	142	56	17	8	3	0	0	3	0	0	
8:	0	0	0	0	0	0	32	465	857	443	146	37	9	1	1	2	0	0	0	0	
9:	0	0	0	0	0	0	6	352	948	518	138	26	3	0	2	0	0	0	0	0	
10:	0	0	0	0	0	0	1	215	1009	618	134	13	3	0	0	0	0	0	0	0	
11:	0	0	0	0	0	0	21	295	750	555	202	96	38	22	9	3	0	0	1	1	
12:	0	0	0	0	0	0	0	3	291	975	532	158	28	6	0	0	0	0	0	0	
13:	0	0	0	0	0	0	0	0	1	129	1117	622	117	7	0	0	0	0	0	0	
14:	0	0	0	0	0	0	37	373	722	521	198	78	34	18	7	3	0	0	1	1	
15:	0	0	0	0	0	0	1	106	663	766	354	85	16	2	0	0	0	0	0	0	
16:	0	0	0	0	0	0	1	7	278	951	639	109	8	0	0	0	0	0	0	0	
17:	0	0	0	0	0	1	80	430	692	555	204	28	3	0	0	0	0	0	0	0	
18:	0	0	0	0	0	0	0	7	100	818	909	143	16	0	0	0	0	0	0	0	
19:	0	1	2	1	5	8	31	99	185	321	329	281	246	171	100	54	36	33	26	64	
20:	0	0	0	0	0	0	0	0	0	0	1993	0	0	0	0	0	0	0	0	0	
21:	0	0	2	0	2	6	26	85	259	498	576	308	119	38	25	14	12	8	2	13	
22:	0	0	2	0	3	3	24	105	335	561	491	236	100	44	26	16	9	9	8	21	

Table 8 (Continued)

23:	0	0	2	0	0	3	16	56	164	357	501	379	201	123	74	37	25	16	13	26
24:	0	0	1	1	0	5	17	84	278	578	525	272	102	49	22	17	10	8	3	21
25:	0	0	2	0	2	6	22	82	269	499	562	313	124	44	27	11	9	10	0	11
26:	0	0	2	0	2	4	24	106	330	589	510	220	97	40	14	15	11	5	7	17

Table 9

MODEL ASSIGNMENT ANALYSIS - PERISHABLE SUBSISTENCE:
LEAD TIME DEMAND - INVIDUAL VS.
BASE MODEL PERFORMANCE AND
PERFORMANCE OF ASSIGNMENT ALLOCATION

INDIVIDUAL MODEL V.S. BASE MODEL

1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
102.4	88.0	92.8	97.9	96.3	88.0	86.7	86.9	87.6	88.6	91.4	98.3	108.7	90.0	93.6	98.0	87.3	100.6	115.7	100.0
39.8	15.8	23.3	31.4	30.6	15.9	12.0	10.0	8.6	7.5	13.6	8.7	6.6	13.3	9.4	7.5	10.4	6.8	32.3	.0
-.06	.76	.31	.07	.12	.75	1.10	1.31	1.44	1.53	.63	.20	-1.32	.75	.68	.26	1.22	-.08	-.49	.00

21	22	23	24	25	26
103.7	102.7	111.9	103.4	103.3	101.5
21.5	24.6	24.1	21.5	18.8	20.7
-.17	-.11	-.49	-.16	-.17	-.07

REDUCTION IN BASE RMSE FOR ASSIGNED MODELS

MODEL	100	90	80	70	60	50	40	30	20	10	0	-10	-20	-30	-40	-50	-60	-70	-80	-90	-100		
2:	0	0	0	0	0	4	126	363	241	58	4	0	0	0	0	0	0	0	0	0		796	22.0
7:	0	0	0	0	0	1	12	166	394	215	34	1	0	0	0	0	0	0	0	0		823	13.9
18:	0	0	0	0	0	0	0	3	13	76	75	1	0	0	0	0	0	0	0	0		168	1.6
19:	0	1	2	1	5	6	19	28	8	2	0	0	0	0	0	0	0	0	0	0		72	32.8
21:	0	0	0	0	0	3	11	22	46	38	12	2	0	0	0	0	0	0	0	0		134	13.9
	0	1	2	1	5	14	168	581	703	389	125	4	0	0	0	0	0	0	0	0			

Table 10

MODEL ASSIGNMENT ANALYSIS - PERISHABLE SUBSISTENCE: LEAD TIME DEMAND - ASSIGNMENT CONTRIBUTION MATRIX

ASSIGNMENT CONTRIBUTION

1	499	4.6	1.2	1.2																			
2	796	-3.1	-1.2	.3	-1.2																		
3	500	4.2	1.0	1.6	.3	1.0																	
4	465	4.7	1.1	1.4	.2	1.5	1.1																
5	504	4.3	1.1	1.7	.3	1.7	1.7	1.1															
6	581	1.8	.5	1.3	-.3	1.2	1.3	1.3	.5														
7	823	-3.8	-1.6	.3	-13.5	.1	.2	.3	.1	-1.6													
8	410	1.6	.3	1.5	-.8	1.4	1.4	1.4	.9	.0	.3												
9	388	2.5	.5	1.6	-.7	1.5	1.6	1.5	1.0	.0	.5	.5											
10	364	2.8	.5	1.7	-.7	1.5	1.6	1.6	1.0	-.2	.6	.6	.5										
11	141	3.7	.3	1.4	-.9	1.3	1.4	1.4	.8	-1.0	.5	.6	.6	.3									
12	60	3.4	.1	1.3	-1.1	1.1	1.2	1.2	.6	-1.4	.4	.5	.5	.3	.1								
13	6	4.0	.0	1.2	-1.2	1.1	1.1	1.1	.6	-1.5	.3	.5	.5	.3	.1	.0							
14	185	3.3	.3	1.5	-.8	1.3	1.4	1.4	.8	-.8	.5	.6	.7	.4	.4	.3	.3						
15	159	4.2	.3	1.5	-.9	1.4	1.4	1.4	.9	-.9	.5	.6	.6	.5	.3	.3	.5	.3					
16	102	3.9	.2	1.4	-1.0	1.2	1.3	1.3	.7	-1.2	.5	.6	.6	.4	.2	.2	.5	.4	.2				
17	428	3.1	.7	1.7	-.3	1.6	1.7	1.6	1.1	.0	.8	.9	.9	.8	.7	.7	.8	.8	.8	.7			
18	168	-9.7	-.8	.4	-2.1	.2	.3	.3	-.3	-3.2	-.2	.2	.3	-.3	-.3	-.5	-.3	.0	.0	.4	-.8		
19	72	-12.5	-.5	.7	-1.8	.6	.7	.6	.1	-2.0	-.1	.0	.1	-.2	-.4	-.4	-.1	-.1	-.3	.2	-1.3	-.5	
20	127	3.3	.2	1.4	-1.0	1.2	1.3	1.3	.7	-1.3	.5	.6	.6	.5	.3	.2	.5	.5	.4	.8	.0	-.2	.2
21	134	-7.2	-.5	.7	-1.9	.6	.7	.6	.1	-2.2	-.1	.0	.1	-.2	-.4	-.5	-.1	-.1	-.3	.2	-1.6	-1.8	-.2
				-.5																			
22	69	3.3	.1	1.3	-1.1	1.1	1.2	1.2	.6	-1.4	.4	.6	.6	.4	.2	.1	.4	.4	.3	.8	-.6	-.3	.3
				-.2	.1																		
23	52	5.0	.1	1.3	-1.1	1.2	1.2	1.2	.7	-1.4	.5	.6	.6	.4	.2	.1	.4	.5	.3	.8	-.6	-.3	.3
				-.1	.2	.1																	
24	83	4.9	.2	1.4	-1.0	1.2	1.3	1.3	.7	-1.3	.5	.7	.7	.5	.3	.2	.5	.5	.4	.9	-.5	-.2	.4
				-.1	.3	.3	.2																
25	99	2.4	.1	1.3	-1.1	1.2	1.2	1.2	.7	-1.4	.4	.6	.6	.4	.2	.1	.4	.4	.3	.8	-.7	-.3	.3
				.0	.2	.2	.3	.1															
26	89	3.4	.2	1.3	-1.0	1.2	1.3	1.2	.7	-1.4	.5	.6	.6	.4	.2	.2	.5	.5	.3	.8	-.5	-.2	.4
				-.1	.2	.2	.2	.2	.2														

The first column of the matrix in Table 10 provides the model number. The second column contains the assignment frequency for assigned models or the frequency which the unanalyzed models outperformed any in the assigned group for the unanalyzed models. For example, 796 times out of 1993, model 2 (12 month average) outperformed any in the assigned group.

The third column provides the percentage improvement in base RMSE over the assigned group for the unanalyzed models on those series they performed better. For models in the assigned group, the third column provides the average loss of performance on the assigned subclass of items if the model were deleted from the assigned group.

For unanalyzed models, the fourth column contains the additional average performance to be gained across the entire class of items if the unanalyzed model were added to the subgroup. For assigned models, the fourth column contains the loss of performance across the entire class of items should the models be deleted from the group. With column 5, the assignment switching matrix (# models x # models) begins. The purpose of the assignment switching matrix is to perform sensitivity analyses on the selection of the assigned model group with at most two models at a time. The diagonal of the assignment switching matrix is equivalent to column 4. An example of the use of the assignment switching matrix is as follows:

a. Both models 1 and 5 (global mean and SES(.05)) are unanalyzed in the test group. Individually, adding model 1 would provide a 1.2 percent additional reduction in RMSE while individually, model 5 could add 1.1 percent. However, the additional performance (1.7 percent) achieved by including both models is not additive. This indicates that often both the global mean and SES(.05) perform similarly on most items which is not surprising. Performance can be additive when the two models perform well on distinctly different series.

b. Models 7 (SES(.15)) and 19 (LAST YEAR) are both assigned. If model 7 was deleted from the assigned group, a 1.6 percent reduction in performance would be encountered. If model 19 was deleted from the group, a .5 percent reduction is expected. However, when both are deleted, a 2.0 percent reduction in performance would be encountered. This indicates that model 19 is performing well when model 7 isn't and that the effects of their deletion is almost additive.

c. Model 7 (SES(.15)) is assigned, however, model 12 (DES(.20)) is not. To measure the effect of switching models 7 and 12, go to row 12, column 11, of the assignment contribution matrix (-1.4). This indicates that if DES(.20) were substituted for SES(.15) in the assigned group, a degradation of 1.4 percent in performance would occur.

d. Models 18 and 19 are known as naive methods and require no calculations. In the model assignments in this study, several heuristics were decided upon as follows:

(1) Do not assign long-term moving averages or global mean due to data storage considerations or high mean bias.

(2) Assign either single, double, DLA formulations, and adaptive exponential smoothing using one or the combined exponential smoothing model but not both.

(3) Do not employ exponential smoothing with two distinct fixed smoothing constants due to the uncertainty of which to use in the future.

(4) Use the simple naive models as a baseline to measure performance due to ease of use. In forecasting literature performance is often measured by the Theil U Statistic, the ratio of the RMSE of the forecast model to the RMSE of no change extrapolation (Model 18).

(5) Use the simplest, most effective nonnaive seasonal model available, which in this study was the AR1 with lag seasonal term. The AR1 lag is, in effect, a regression using a naive monthly and the last year forecasts as independent variables.

The first of four sections of Table 11 indicates the mean bias (e.g., Theil's bias proportion averaged across all items) and the standard deviation about the mean bias for individual model assignment. Long-term averages such as model 1 - the Global mean and model 4 - the 36-month average exhibit high mean bias as can be observed here. These should be corrected for bias prior to their use.

The second section of Table 11 provides the mean bias (e.g., Theil's bias proportion averaged over assigned subclasses for each assigned model) and the standard deviation about that mean.

The third section of Table 11 reflects the performance distribution of the assigned group in deciles.

The fourth section of Table 11 indicates the future performance of the base model against the assigned set or the amount of error we accept using the base model in lieu of the assigned model group. The entire model assignment analysis is repeated for procurement cycle demand in Tables 12 through 15.

Optimal Linear Corrections and corrections for mean bias require the storage of extra data elements to perform forecast adjustments as do Autoregressive Harmonic Models. Nonetheless, based on the heuristics above, the assigned set appears optimal for perishable subsistence items.

Assignment of the forecast models may be made individually (e.g., simply replacement of present method by another or by a group).

Only methods that resulted in significant reduction in standard deviation of lead time and procurement cycle demand were accepted for assignment. If a model was unacceptably biased ($U^M > .2$), it was rejected. However, in this case, a pre-correction for mean bias could be employed. This approach would result in even greater reductions in standard deviation of lead time and procurement cycle demand.

2. Construction of Model Groups for the Subsistence Commodity.

The solution of the model assignment problem requires a procedure to rank the competing models against the current method for a specified group of items. It

Table 11

MODEL ASSIGNMENT ANALYSIS - PERISHABLE SUBSISTENCE:
LEAD TIME DEMAND - BIAS AND OVERALL
PERFORMANCE OF GROUP ASSIGNMENT

MODEL BIAS

1	.245	.242
2	.059	.096
3	.126	.164
4	.182	.203
5	.186	.208
6	.091	.131
7	.058	.096
8	.041	.075
9	.032	.062
10	.026	.052
11	.042	.083
12	.010	.022
13	.005	.012
14	.046	.086
15	.016	.031
16	.012	.024
17	.028	.048
18	.013	.033
19	.083	.118
20	.010	.024
21	.067	.096
22	.060	.092
23	.067	.095
24	.056	.085
25	.063	.092
26	.058	.088

ASSIGNMENT BIAS

2	.046	.071
7	.045	.069
18	.054	.077
19	.043	.063
21	.065	.087

PERCENT REDUCTION IN BASE MODEL S.D.

MODEL 100 90 80 70 60 50 40 30 20 10 0 -10 -20 -30 -40 -50 -60 -70 -80 -90 -100
0 1 2 1 5 14 168 581 703 389 125 4 0 0 0 0 0 0 0 0

AVERAGE BASE S.D./ASSIGNED S.D. =122.7

MODEL 100 90 80 70 60 50 40 30 20 10 0 -10 -20 -30 -40 -50 -60 -70 -80 -90 -100
0 0 0 0 0 0 0 0 3 124 342 499 466 306 157 54 21 7 3 11

Table 12

MODEL ASSIGNMENT ANALYSIS - PERISHABLE SUBSISTENCE: PROCUREMENT CYCLE DEMAND - ASSIGNMENT OCCURRENCE AND INDIVIDUAL ASSIGNMENT DISTRIBUTION MATRICES

TROOP ISSUE AND BRAND NAME

PROC CYCLE	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26
2*	282	937	315	289	273	205	865	37	32	22	29	2	0	61	23	9	117	1	26	5	45	17	0	11	0	13
7*	300	819	288	292	331	429	873	356	331	288	97	47	9	141	153	117	339	31	0	91	23	5	1	7	1	5
18*	1	1	0	0	2	1	22	7	15	18	5	6	2	6	15	14	15	34	0	28	11	0	1	1	1	0
19*	2	18	2	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	48	0	30	0	0	1	0	1
21*	8	61	8	7	11	6	21	6	10	13	14	4	3	14	15	11	21	10	9	13	:01	1	0	7	0	6
PREFER	593	0	613	589	618	641	0	406	388	341	145	59	14	222	206	151	492	0	0	137	0	23	2	27	2	25
ACCEPT	0	1836	0	0	0	0	1781	0	0	0	0	0	0	0	0	0	0	76	83	0	210	0	0	0	0	0
ASSIGN	0	937	0	0	0	0	873	0	0	0	0	0	0	0	0	0	0	34	48	0	101	0	0	0	0	0

AVERAGE STD DEV INDEX (BASE MODEL 20): 86.6 1993 SERIES ACCEPTED

REDUCTION IN BASE RMSE

MODEL 100 90 80 70 60 50 40 30 20 10 0 -10 -20 -30 -40 -50 -60 -70 -80 90 -100

1:	0	0	0	0	0	3	26	324	593	442	263	124	71	45	17	22	11	12	9	31
2:	0	0	0	0	0	1	26	366	819	518	188	50	16	4	3	1	1	0	0	0
3:	0	0	0	0	0	0	36	377	682	487	220	98	43	22	11	4	7	3	0	3
4:	0	0	0	0	0	1	24	351	623	474	233	129	55	37	21	14	8	5	3	15
5:	0	0	0	0	1	2	24	304	720	481	225	107	50	25	14	12	5	6	6	11
6:	0	0	0	0	0	0	7	288	949	514	162	42	18	6	3	2	1	1	0	0
7:	0	0	0	0	0	0	2	183	1057	592	123	27	6	1	2	0	0	0	0	0
8:	0	0	0	0	0	0	1	73	1101	697	107	11	1	2	0	0	0	0	0	0
9:	0	0	0	0	0	0	0	17	1035	841	89	9	2	0	0	0	0	0	0	0
10:	0	0	0	0	0	0	0	5	826	1079	74	9	0	0	0	0	0	0	0	0
11:	0	0	0	0	0	0	0	39	751	847	256	64	21	9	3	2	0	0	0	1
12:	0	0	0	0	0	0	0	0	20	718	1028	196	22	8	1	0	0	0	0	0
13:	0	0	0	0	0	0	0	0	0	16	417	1055	430	73	2	0	0	0	0	0
14:	0	0	0	0	0	0	1	99	889	742	212	36	6	4	2	0	1	0	0	1
15:	0	0	0	0	0	0	0	6	317	1304	334	27	3	1	1	0	0	0	0	0
16:	0	0	0	0	0	0	0	0	67	1087	818	19	2	0	0	0	0	0	0	0
17:	0	0	0	0	0	1	3	215	904	723	140	7	0	0	0	0	0	0	0	0
18:	0	0	0	0	0	0	0	0	0	19	746	1165	61	2	0	0	0	0	0	0
19:	0	0	2	1	6	8	10	63	119	226	409	382	303	218	119	58	32	12	12	13
20:	0	0	0	0	0	0	0	0	0	0	1993	0	0	0	0	0	0	0	0	0
21:	0	0	0	2	3	7	12	70	177	477	710	341	110	36	15	9	9	4	0	11
22:	0	0	0	0	0	1	2	30	147	355	540	404	247	141	48	25	13	12	10	18

Table 12 (Continued)

23	0	0	0	0	0	0	0	1	4	6	17	23	37	52	64	77	84	90	101	1437
24	0	0	0	0	0	0	4	20	148	356	493	429	255	133	75	24	26	6	8	16
25	0	0	0	0	0	0	0	1	4	6	17	23	36	51	63	79	85	90	99	1439
26	0	0	0	0	1	0	2	25	147	357	544	418	244	134	53	24	16	7	6	15

Table 13

MODEL ASSIGNMENT ANALYSIS - PERISHABLE SUBSISTENCE: PROCUREMENT CYCLE DEMAND - INDIVIDUAL VS. BASE PERFORMANCE AND PERFORMANCE OF ASSIGNMENT ALLOCATION

INDIVIDUAL MODEL V.S. BASE MODEL

1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
97.4	88.7	91.4	94.5	93.7	89.0	88.8	89.4	90.4	91.4	93.6	102.6	115.7	91.2	95.2	99.0	89.0	111.4	115 8	100.0
26.5	10.7	15.4	20.8	21.3	10.5	7.9	6.5	5.5	4.7	10.2	6.5	7.3	8.9	5.9	4.8	7.5	4.9	23.6	.0
.10	1.05	.56	.26	.30	1.04	1.42	1.63	1.76	1.84	.63	-.39	-2.16	.99	.81	.20	1.48	-2.34	-.67	.00

21	22	23	24	25	26
104.3	112.1	242.9	112.3	243.0	111.4
19.0	24.9	82.1	20.7	82.1	21.0
-.22	-.49	-1.74	-.60	-1.74	-.54

REDUCTION IN BASE RMSE FOR ASSIGNED MODELS

MODEL	100	90	80	70	60	50	40	30	20	10	0	-10	-20	-30	-40	-50	-60	-70	-80	-90	-100		
2:		0	0	0	0	0	1	16	300	518	97	5	0	0	0	0	0	0	0	0	0	937	17.4
7:		0	0	0	0	0	0	1	22	355	403	86	6	0	0	0	0	0	0	0	0	873	8.5
18:		0	0	0	0	0	0	0	0	0	6	27	1	0	0	0	0	0	0	0	0	34	-3.1
19:		0	0	2	1	6	4	9	22	4	0	0	0	0	0	0	0	0	0	0	0	48	35.1
21:		0	0	0	0	1	4	6	23	24	30	13	0	0	0	0	0	0	0	0	0	101	14.8
		0	0	2	1	7	9	32	367	901	536	131	7	0	0	0	0	0	0	0	0		

Table 14

MODEL ASSIGNMENT ANALYSIS - PERISHABLE SUBSISTENCE:
PROCUREMENT CYCLE DEMAND - ASSIGNMENT CONTRIBUTION MATRIX

ASSIGNMENT CONTRIBUTION

1	593	4.0	1.2	1.2																									
2	937	-2.8	-1.3	.3	-1.3																								
3	613	3.4	1.0	1.6	.4	1.0																							
4	589	3.8	1.1	1.4	.3	1.5	1.1																						
5	618	3.6	1.1	1.6	.3	1.6	1.6	1.1																					
6	641	1.6	.5	1.3	-.3	1.2	1.2	1.2	.5																				
7	873	-2.8	-1.2	.5	-16.1	.3	.4	.5	.2	-1.2																			
8	406	1.4	.3	1.5	-1.0	1.3	1.4	1.4	.8	.0	.3																		
9	388	2.1	.4	1.6	-.9	1.5	1.5	1.5	.9	.0	.4	.4																	
10	341	2.7	.5	1.6	-.9	1.5	1.6	1.6	1.0	.0	.5	.5	.5																
11	145	3.2	.2	1.4	-1.1	1.3	1.3	1.4	.7	-.7	.4	.5	.6	.2															
12	59	3.9	.1	1.3	-1.2	1.2	1.2	1.2	.6	-1.0	.3	.4	.5	.3	.1														
13	14	3.0	.0	1.2	-1.3	1.1	1.1	1.2	.5	-1.2	.3	.4	.5	.2	.1	.0													
14	222	2.7	.3	1.5	-.9	1.4	1.4	1.4	.8	-.5	.5	.6	.6	.4	.4	.3	.3												
15	206	3.8	.4	1.6	-.9	1.4	1.5	1.5	.9	-.4	.5	.6	.6	.5	.4	.4	.6	.4											
16	151	4.2	.3	1.5	-1.0	1.4	1.4	1.4	.8	-.6	.5	.5	.6	.5	.3	.3	.6	.5	.3										
17	492	2.8	.7	1.7	-.4	1.6	1.6	1.6	1.0	.2	.8	.8	.9	.8	.7	.7	.8	.8	.8	.7									
18	34	-8.4	-.1	1.0	-1.5	.9	1.0	1.0	.4	-1.5	.2	.3	.4	.1	.0	-.1	.2	.3	.3	.6	-.1								
19	48	-10.6	-.3	.9	-1.7	.8	.9	.9	.3	-1.5	.0	.2	.2	.0	-.1	-.2	.0	.1	.1	.4	-.4	-.3							
20	137	3.6	.2	1.4	-1.1	1.3	1.4	1.4	.8	-.7	.4	.5	.5	.4	.3	.2	.5	.5	.4	.8	.2	.0	.2						
21	101	-5.2	-.3	.9	-1.8	.8	.9	.9	.3	-1.5	.0	.2	.2	.0	-.1	-.2	.1	.2	.1	.5	-.5	-.9	.0	-.3					
22	23	4.1	.0	1.2	-1.2	1.1	1.2	1.2	.6	-1.2	.3	.5	.5	.3	.2	.1	.3	.4	.4	.7	-.1	-.2	.3	-.2	.0				
23	2	8.8	.0	1.2	-1.3	1.1	1.1	1.1	.5	-1.2	.3	.4	.5	.2	.1	.0	.3	.4	.3	.7	-.1	-.2	.3	-.3	.1	.0			
24	27	5.0	.1	1.2	-1.2	1.1	1.2	1.2	.6	-1.1	.3	.5	.5	.3	.2	.1	.4	.4	.4	.7	-.1	-.2	.3	-.2	.1	.1	.1		
25	2	8.8	.0	1.2	-1.3	1.1	1.1	1.1	.5	-1.2	.3	.4	.5	.2	.1	.0	.3	.4	.3	.7	-.1	-.2	.3	-.3	.1	.0	.1	.0	
26	25	3.8	.0	1.2	-1.2	1.1	1.2	1.2	.6	-1.2	.3	.5	.5	.3	.2	.1	.3	.4	.4	.7	-.1	-.2	.3	-.2	.1	.1	.1	.1	.0

Table 15

MODEL ASSIGNMENT ANALYSIS - PERISHABLE SUBSISTENCE: PROCUREMENT CYCLE DEMAND - BIAS AND OVERALL PERFORMANCE OF GROUP ASSIGNMENT

MODEL BIAS

1	.190	.210
2	.050	.084
3	.099	.138
4	.141	.172
5	.141	.173
6	.072	.109
7	.048	.082
8	.036	.067
9	.029	.056
10	.025	.049
11	.037	.071
12	.010	.020
13	.006	.012
14	.037	.071
15	.015	.031
16	.013	.027
17	.029	.051
18	.009	.020
19	.052	.080
20	.013	.028
21	.050	.078
22	.053	.082
23	.844	.103
24	.053	.079
25	.844	.103
26	.051	.080

ASSIGNMENT BIAS

2	7	18	19	21
.038	.046	.053	.040	.055
.058	.074	.063	.063	.076

PERCENT REDUCTION IN BASE MODEL S.D.

MODEL	100 to 90	90 to 80	80 to 70	70 to 60	60 to 50	50 to 40	40 to 30	30 to 20	20 to 10	10 to 0	0 to -10	-10 to -20	-20 to -30	-30 to -40	-40 to -50	-50 to -60	-60 to -70	-70 to -80	-80 to -90	-90 to -100
	0	0	2	1	7	9	32	367	901	536	131	7	0	0	0	0	0	0	0	0

AVERAGE BASE S.D./ASSIGNED S.D. =117.1

MODEL	100 to 90	90 to 80	80 to 70	70 to 60	60 to 50	50 to 40	40 to 30	30 to 20	20 to 10	10 to 0	0 to -10	-10 to -20	-20 to -30	-30 to -40	-40 to -50	-50 to -60	-60 to -70	-70 to -80	-80 to -90	-90 to -100
	0	0	0	0	0	0	0	0	6	131	452	706	459	164	47	8	1	5	1	13

is necessary to test individual model assignments across the entire subsistence commodity and to test groups of competing models and their interactions. The authors designed software to construct a group of models for any set of subsistence items. The model assignment analysis technique will be used to construct various model groups for perishable and semiperishable subsistence, respectively.

Due to the large number of models to be evaluated, initial screening was necessary to develop a final model test set from which to select a model group. Fourteen model test sets are described in Appendix N. There was only a 3% to 5% variation in performance (RMSE reduction) among the model test sets when all models were assigned. Model test set 13 resulted in the greatest reduction in RMSE. Model test set 13 was then adjusted to determine if improvement could be achieved by the addition of exponential smoothing techniques. The resultant test set contains 26 models including model test set 13 (the harmonic models were dropped out of Model Test Set 13 as they provided little or no additional improvement), single, double, and adaptive exponential smoothing and the COMBINED model. This test set is used to develop model groups for assignment to subsistence commodity and is referenced in the model assignment reports as "MODELS ON FILE".

The construction of the model groups for the perishable and semiperishable item classes from individual to final group will now be described. (Assignment of the forecast models may be made individually (e.g., simply replace the present method by another) or as a group.

Using a model assignment analysis report, the performance statistics on the five best individuals models for perishable and semiperishable subsistence are derived. These performance statistics include mean reduction in RMSE, standard deviation about the mean reduction and the mean bias. Table 16 provides these performance statistics for the five best individual models.

Table 16

BEST INDIVIDUAL FORECAST PERFORMANCES FOR THE SUBSISTENCE COMMODITY

Subsistence Category

Lead Time Demand

Perishable Model	Mean Reduction in RMSE	Std Dev	Mean Bias	SemiPerishable Model	Mean Reduction in RMSE	Std Dev	Mean Bias
SES(.15)	13.3	12.0	.058	COMBINED	8.2	9.6	.056
SES(.20)	13.1	10.0	.041	SES(.15)	5.6	10.9	.103
COMBINED	12.7	10.4	.028	12 Mo Avg	5.2	14.2	.100
SES(.25)	12.4	8.6	.032	SES(.20)	4.2	7.3	.074
12 Mo Avg	12.0	15.7	.059	SES(.10)	3.0	20.2	.164

Procurement Cycle Demand

Perishable Model	Mean Reduction in RMSE	Std Dev	Mean Bias	SemiPerishable Model	Mean Reduction in RMSE	Std Dev	Mean Bias
12 Mo Avg	11.3	10.7	.050	COMBINED	5.8	7.6	.064
SES(.15)	11.2	7.9	.048	SES(.15)	3.7	8.1	.098
COMBINED	11.0	7.5	.029	12 Mo Avg	3.0	9.9	.095
SES(.10)	11.0	10.5	.072	SES(.10)	2.6	13.8	.140
SES(.20)	10.6	6.5	.036	SES(.20)	1.6	5.6	.078

Figure 3 depicts the distribution of performance for the best individual model assignment, SES(.15), for Perishable Subsistence. Note that while this method is often not the best for individual series, it is a solid performer that rarely performs poorly. On the average, in terms of reduced RMSE related to present DLA methods, it is the best of the models tested for perishable items.

Figure 4 provides the distribution of performance for the best individual model assignment for semiperishable subsistence, COMBINED.

The best individual model provides the greatest improvement in forecast accuracy. The addition of other models results in marginally decreasing improvements in forecast performance.

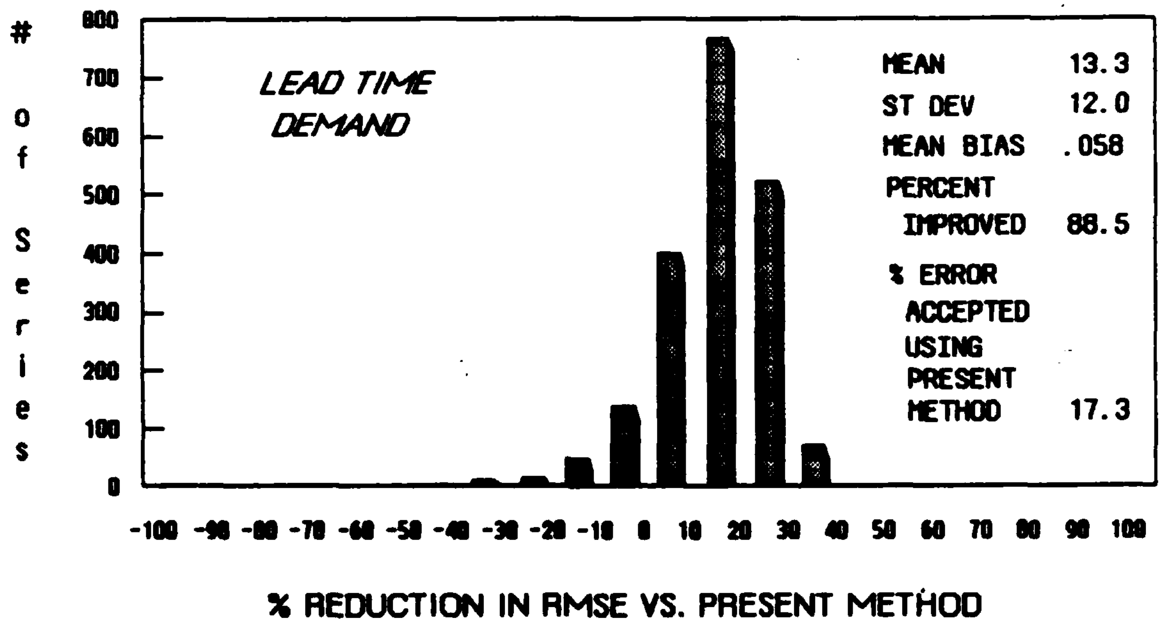
The initial model in the recommended group is the best individual model. The next consideration was to include the naive models. The naive models, LAST LT/PC, represents no change forecasts from the last predictive period's actual demand. The naive model, LAST YEAR, represents no change forecasts from the actual demand last year during the same period.

The naive models serve as benchmarks in a forecasting system for the evaluation of trends and seasonal demand patterns. The best individual and two naive models are designated as the elementary model group.

Appendix D contains the model assignment analyses for the elementary model groups. Table 17 demonstrates the comparative performance of the elementary model group and the best individual model. The Percent Improved columns in Table 17 refers to the percentage of demand series that experienced reduced RMSE over the present DLA forecast RMSE.

FIGURE 3

PERFORMANCE DISTRIBUTION OF
BEST INDIVIDUAL FORECAST MODEL – SES (.15)
PERISHABLE SUBSISTENCE



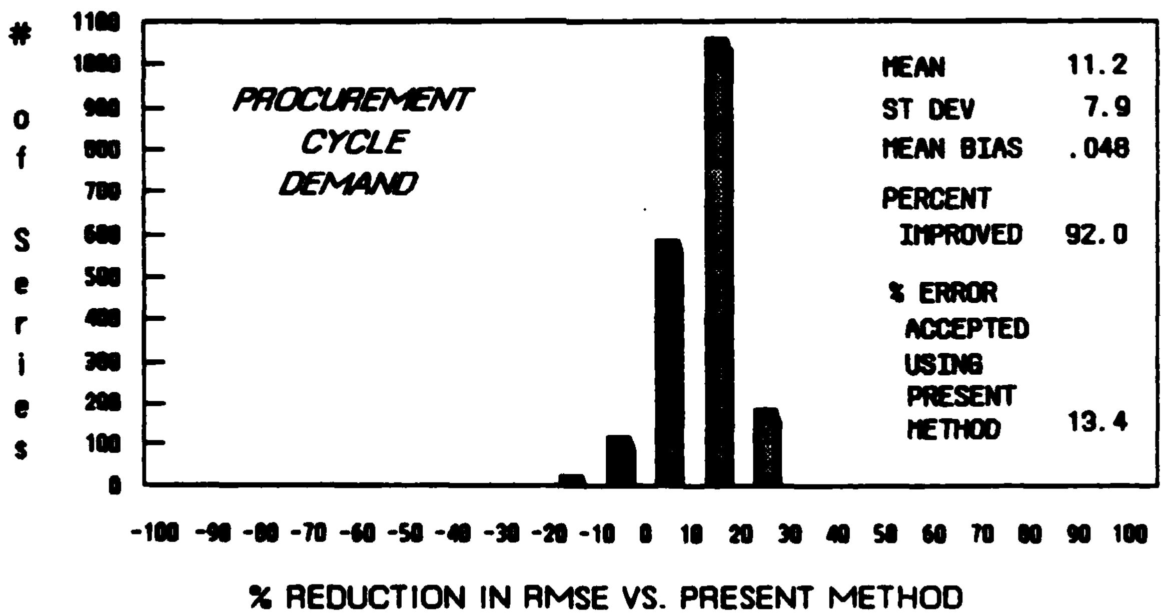
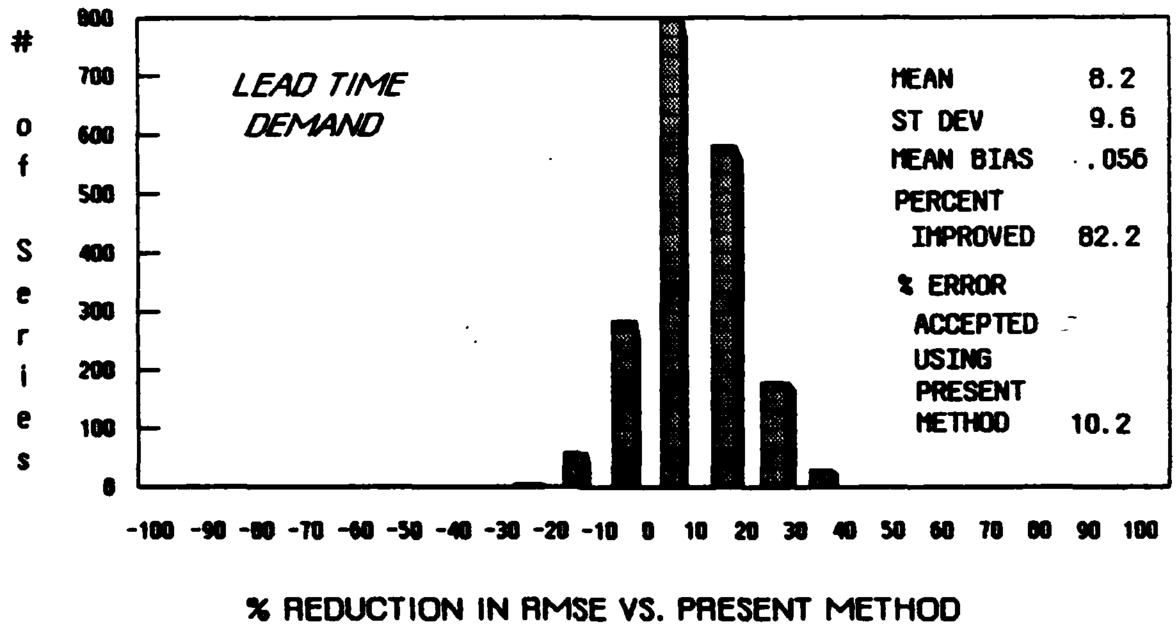


FIGURE 4

PERFORMANCE DISTRIBUTION OF
BEST INDIVIDUAL FORECAST MODEL — COMBINED
SEMIPERISHABLE SUBSISTENCE



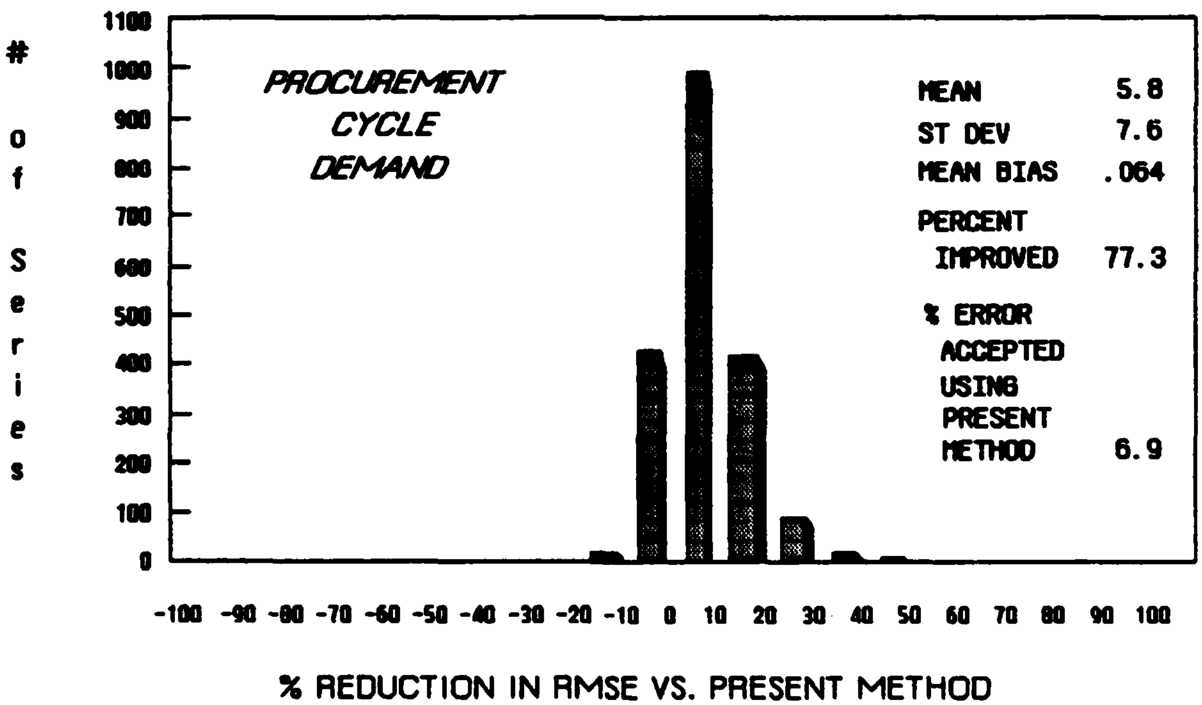


Table 17

COMPARATIVE PERFORMANCE OF BEST INDIVIDUAL AND ELEMENTARY GROUPS OF FORECAST MODELS

Subsistence Category

Lead Time Demand

Model	Perishable: Mean Reduction in RMSE	Perishable: Percent Imprvd.	Perishable: Mean Bias	SemiPerishable: Mean Reduction in RMSE	SemiPerishable: Percent Imprvd.	SemiPerishable: Mean Bias
Best Individual	13.3	88.5	.058	8.2	82.2	.056
Elementary Group	15.4	92.0	.049	10.1	84.7	.063

Procurement Cycle Demand

Model	Perishable: Mean Reduction in RMSE	Perishable: Percent Imprvd.	Perishable: Mean Bias	SemiPerishable: Mean Reduction in RMSE	SemiPerishable: Percent Imprvd.	SemiPerishable: Mean Bias
Best Individual*	11.3	92.0	.048	5.8	77.3	.064
Elementary Group	12.0	92.4	.045	6.6	79.1	.064

* 12-MO AVG was slightly better (.1 percent) than SES(.15) for procurement cycle demand. However, in the interest of parsimony, SES(.15) is chosen as best individual model since it achieved less dispersion of performance.

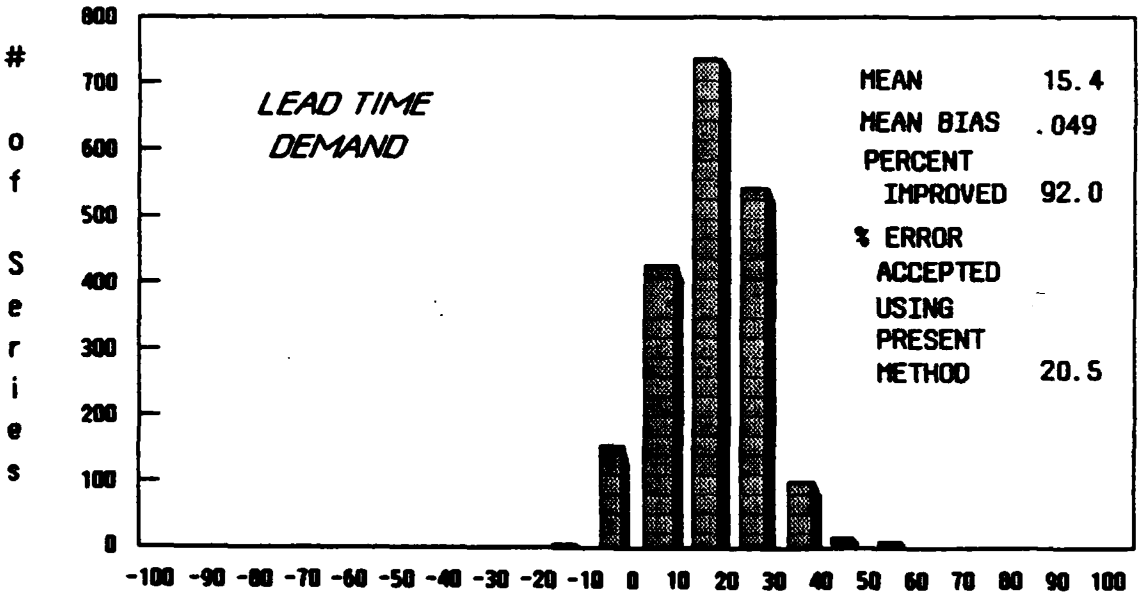
Figures 5 and 6 depict the performance distributions of the elementary model group assignments, for Perishable and Semiperishable Subsistence, respectively.

Examination of the model assignment analyses in Appendix D indicate that additional improvement exceeding a 1 percent reduction in RMSE can be achieved. However, the only model meeting the constraints of the heuristics in Section IIIF1 is the 12-MO AVG. For example, for perishable subsistence, model 1 - GLOBAL MEAN and model 3 - 24-MO AVG, are eliminated due to high mean bias and data storage requirements and SES(.05) is eliminated due to borderline high mean bias and the fact that model 7 - SES(.15) is already assigned. The same rationale holds for the semiperishable model assignment analysis.

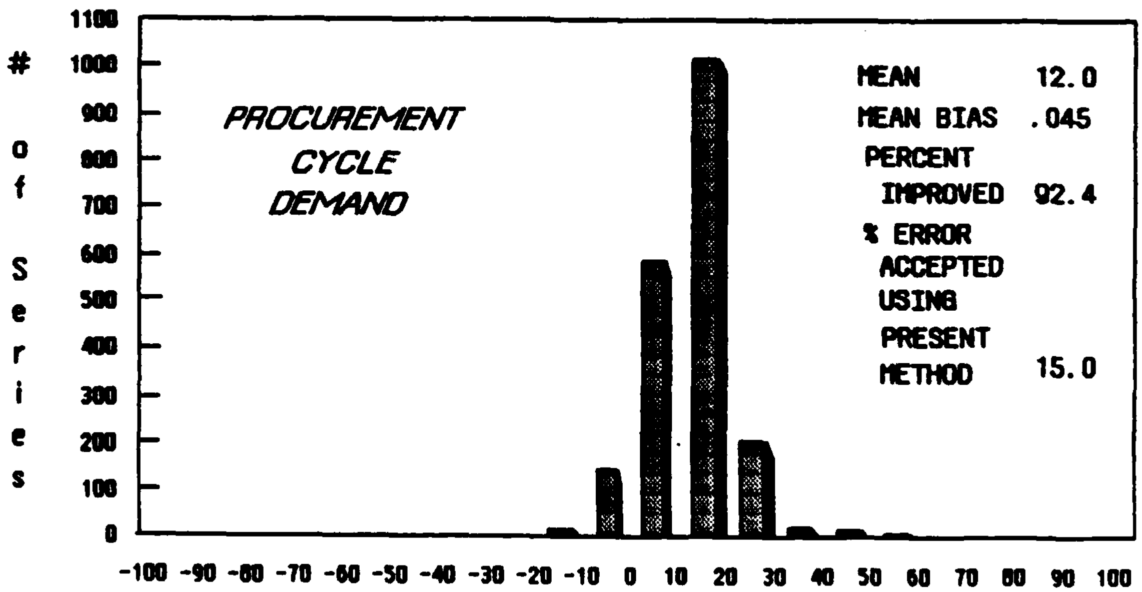
Table 18 presents the comparative performance of the group when the 12-MO AVG is added. This group shall be designated the secondary model group.

FIGURE 5

PERFORMANCE DISTRIBUTION
OF THE ELEMENTARY MODEL GROUP–
PERISHABLE SUBSISTENCE



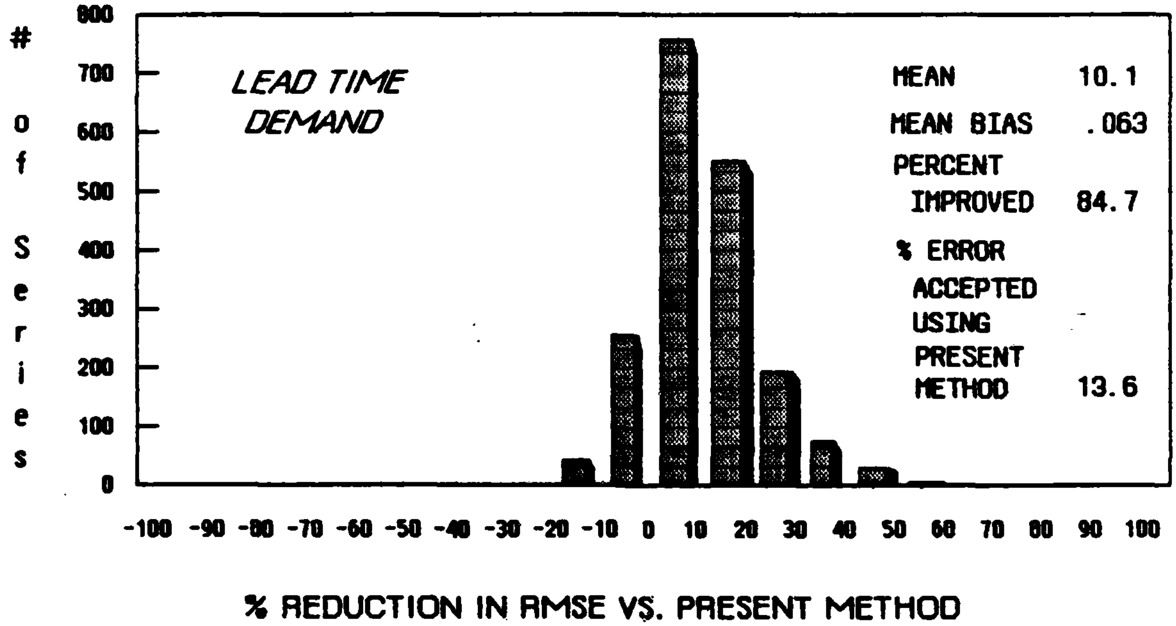
% REDUCTION IN RMSE VS. PRESENT METHOD



% REDUCTION IN RMSE VS. PRESENT METHOD

FIGURE 6

PERFORMANCE DISTRIBUTION OF THE ELEMENTARY MODEL GROUP – SEMIPERISHABLE SUBSISTENCE



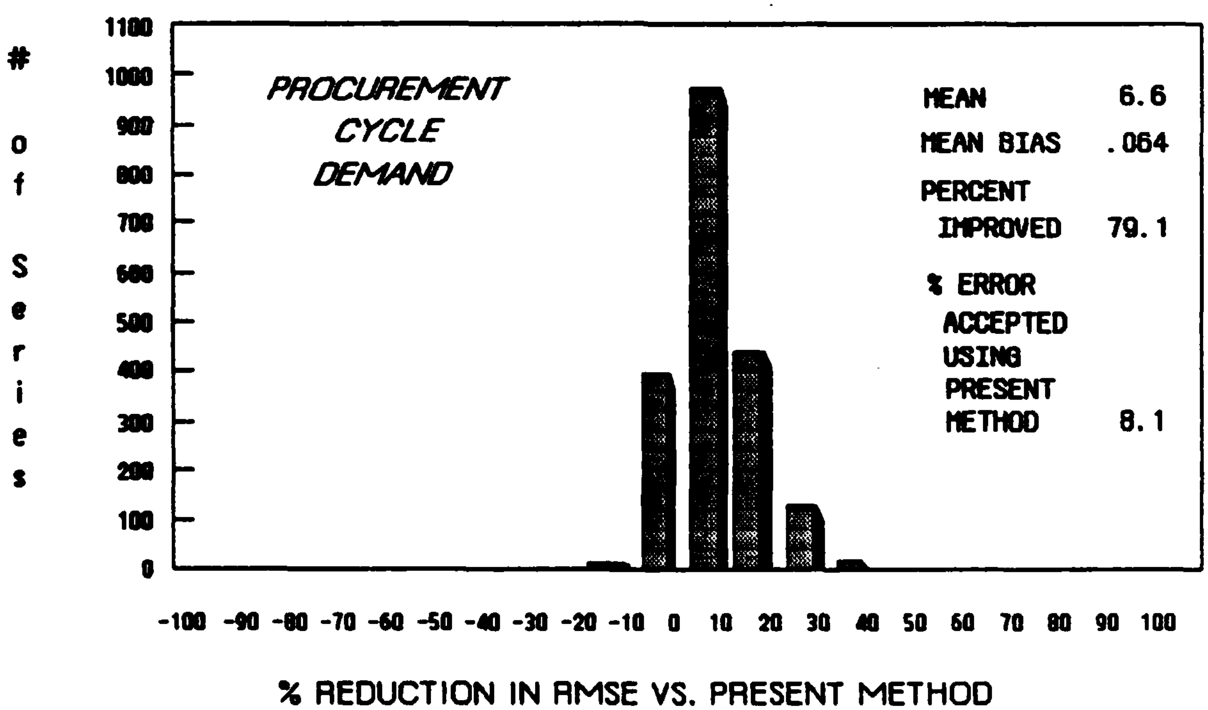


Table 18

COMPARATIVE PERFORMANCE OF BEST INDIVIDUAL, ELEMENTARY, AND SECONDARY GROUPS OF FORECAST MODELS

Subsistence Category

Lead Time Demand

	Perishable			SemiPerishable		
Model	Mean Reduction in RMSE	Percent Imprvd.	Mean Bias	Mean Reduction in RMSE	Percent Imprvd.	Mean Bias
Best Individual	13.3	88.5	.058	8.2	82.2	.056
Elementary Group	15.4	92.0	.049	10.1	84.7	.063
Secondary Group	16.4	92.2	.050	11.6	88.2	.071

Procurement Cycle Demand

	Perishable			SemiPerishable		
Model	Mean Reduction in RMSE	Percent Imprvd.	Mean Bias	Mean Reduction in RMSE	Percent Imprvd.	Mean Bias
Best Individual	11.3	92.0	.048	5.8	77.3	.064
Elementary Group	12.0	92.4	.045	6.6	79.1	.064
Secondary Group	13.2	92.7	.046	7.8	84.9	.074

Figures 7 and 8 depict the performance distributions of the secondary model group assignments, for Perishable and Semiperishable Subsistence, respectively.

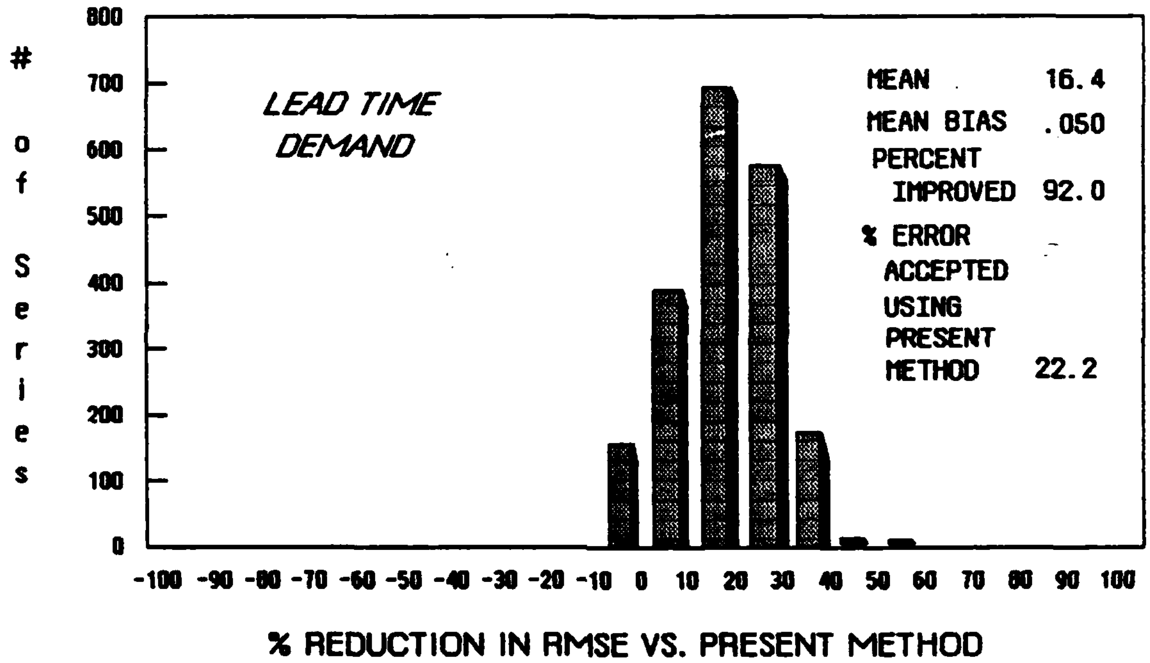
Appendix E contains the model assignment analyses for the secondary model group.

Examination of the model assignment analyses in Appendix E indicate that improvements in forecast accuracy exceeding .75 percent could be achieved, within the constraints of the heuristics in Section IIIF1, only by the addition of an autoregressive seasonal model. Model 25 - SAR1 Lag and Model 21 - AR1 Lag are candidates. Model 25 performs slightly better than Model 21 for lead time demand while Model 21 performs even more better than Model 25 for procurement cycle demand. Due to this fact and in the interest of parsimony, Model 21 was added to the secondary group of models in Appendix E. At this point, we have reached the point of diminishing returns within the constraints of the heuristics in Section IIIF1. The groups, derived from the addition of the AR1 Lag Seasonal Model, to the Secondary groups, will be designated as the Final Model Groups.

Table 19 depicts the performance of the final model groups for the Subsistence Commodity.

FIGURE 7

PERFORMANCE DISTRIBUTION
OF THE SECONDARY MODEL GROUP–
PERISHABLE SUBSISTENCE



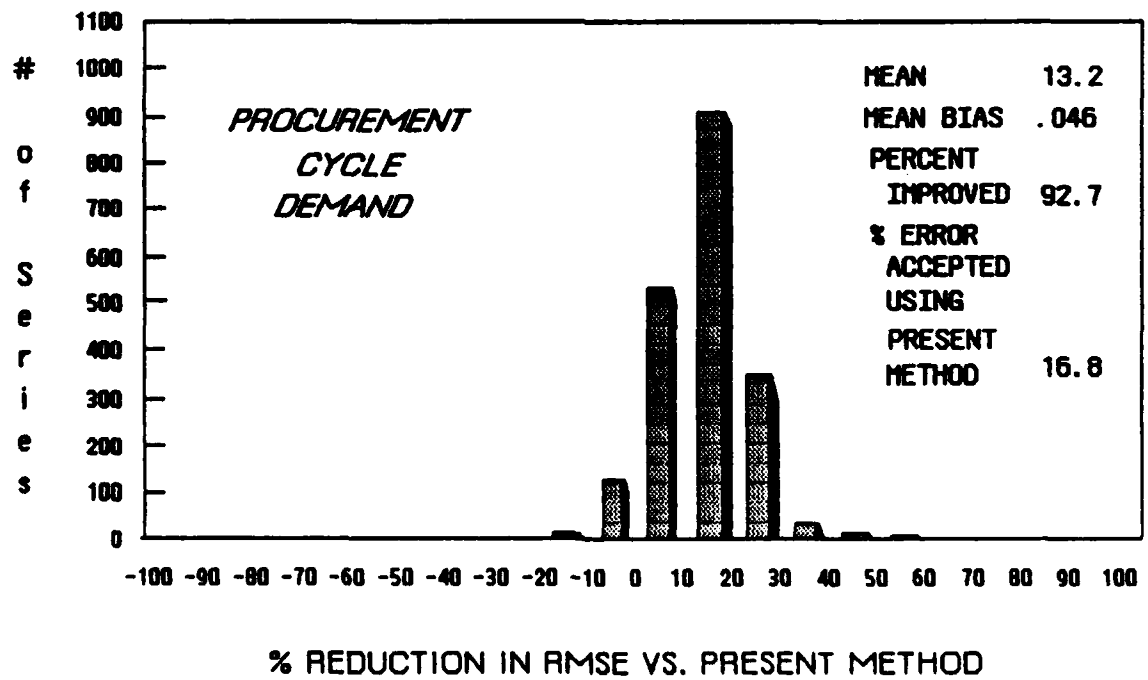
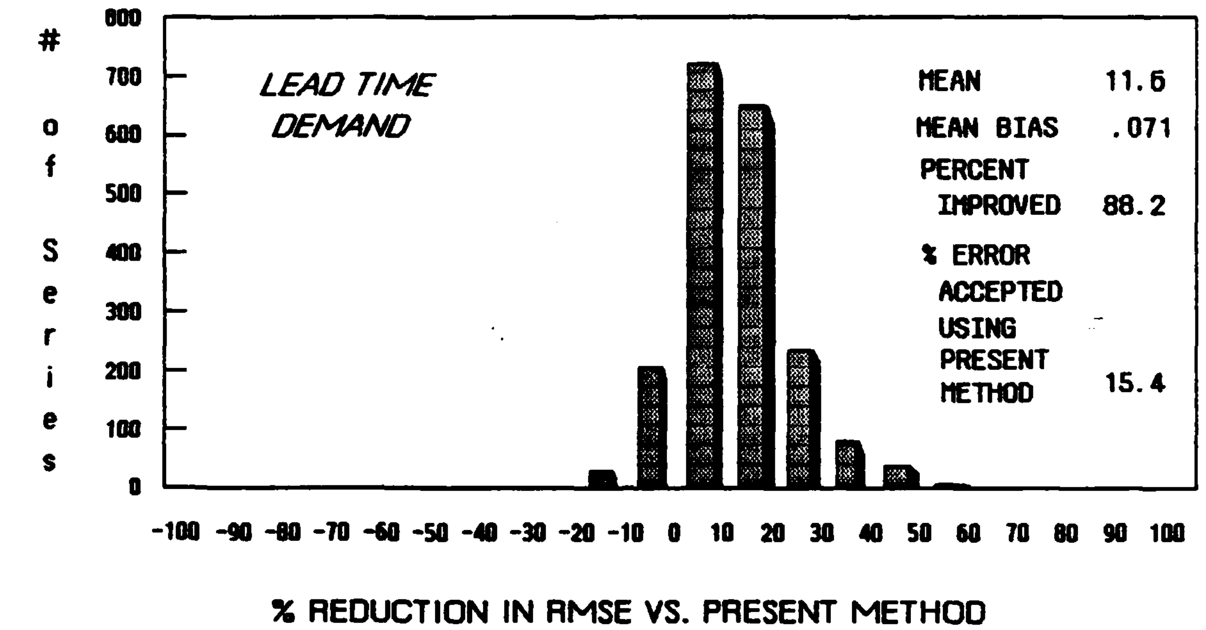


FIGURE 8

PERFORMANCE DISTRIBUTION OF THE SECONDARY MODEL GROUP – SEMIPERISHABLE SUBSISTENCE



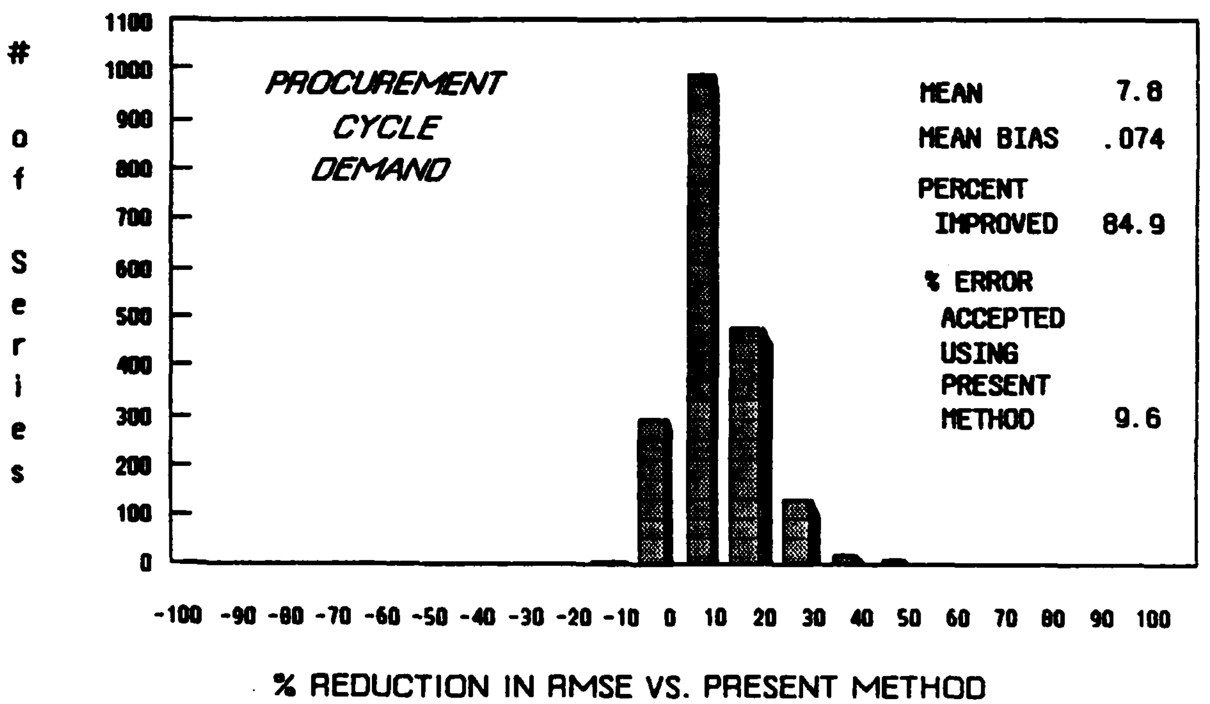


Table 19

PERFORMANCE OF THE FINAL MODEL GROUPS
FOR THE SUBSISTENCE COMMODITY

	Subsistence Category	
	Perishable	Semiperishable
	Lead Time Demand	
Group	12-MO AVG, SES(.15), Last LT, Last Year, AR1 Lag	12-MO AVG, COMBINED, Last LT, Last Year, AR1 Lag
Mean Reduction in RMSE	16.8	12.4
Percent Improved	93.5	90.4
Mean Bias	.047	.068
% Error Accepted Using Present Methods	22.7	16.5
	Procurement Cycle Demand	
Group	12-MO AVG, SES(.15), Last PC, Last Year, AR1 Lag	12-MO AVG, COMBINED, Last PC, Last Year, AR1 Lag
Mean Reduction in RMSE	13.4	8.3
Percent Improved	93.1	86.1
Mean Bias	.043	.065
% Error Accepted Using Present Methods	17.1	10.2

Figures 9 and 10 depict the performance distributions of the final model group assignments, for Perishable and Semiperishable Subsistence, respectively.

Figure 11 provides a comparison of the performance of the best individual, elementary, secondary and final model groups for perishable and semiperishable subsistence, respectively.

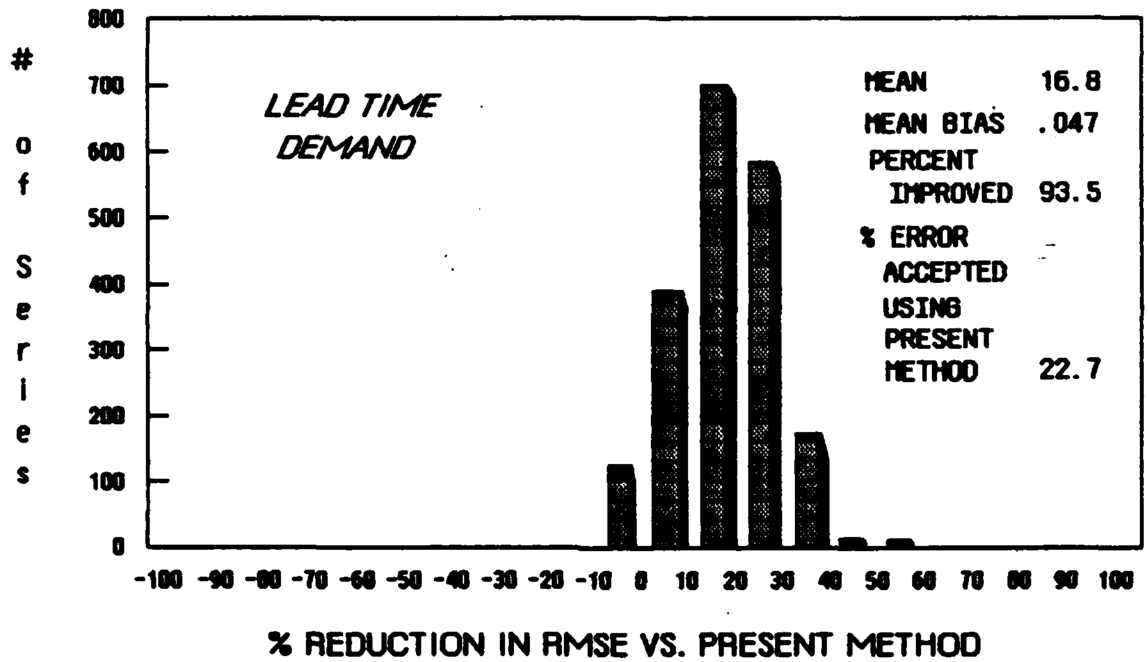
3. Model Assignments and Item Characteristics

The assignment of the final model group differed by item characteristic. This section of the report highlights variations in the assignment and performance of the final model group by the following characteristics:

(1) Item Category - Troop Issue vs. Brand Name
(2) Lead Time and Procurement Cycle Duration

FIGURE 9

PERFORMANCE DISTRIBUTION
OF THE FINAL MODEL GROUP—
PERISHABLE SUBSISTENCE



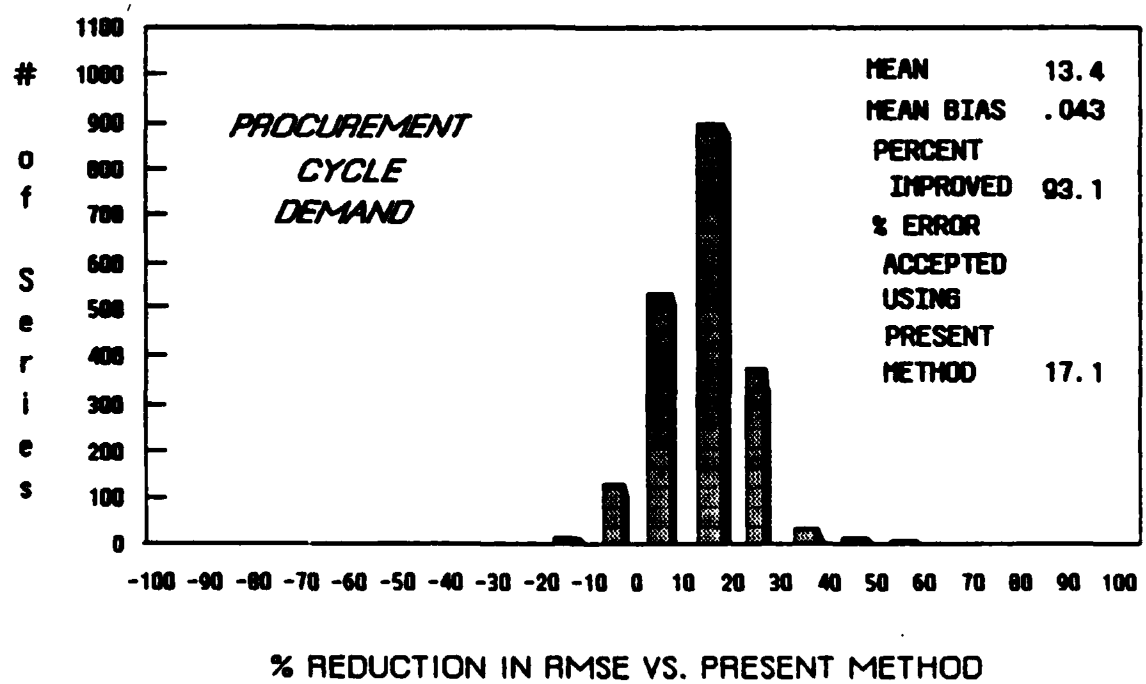
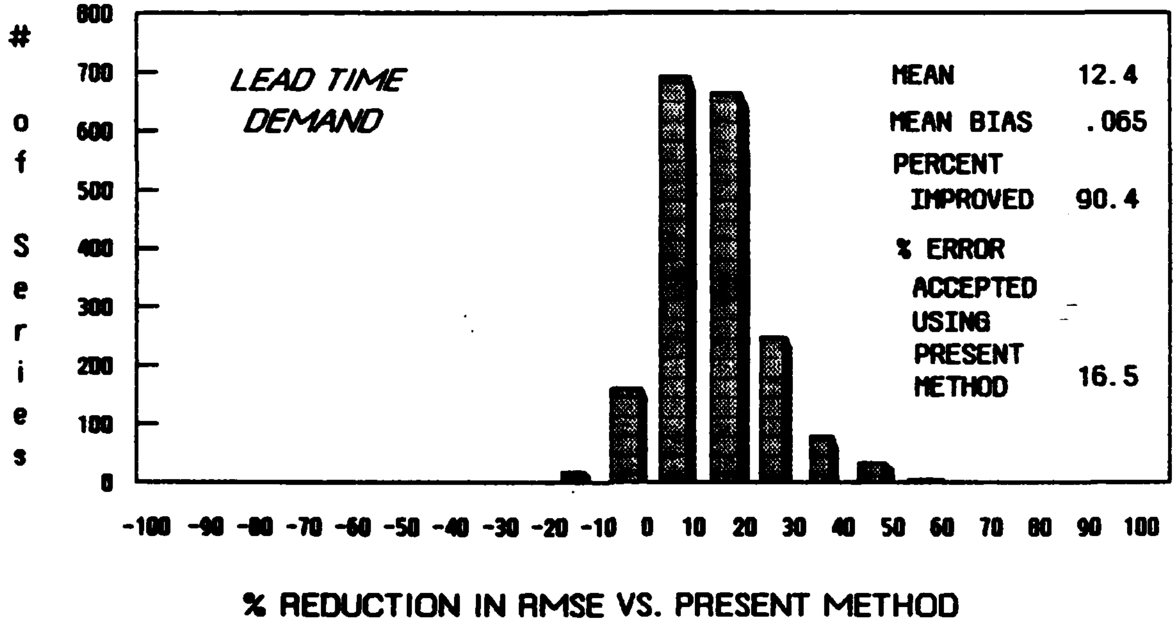


FIGURE 10

PERFORMANCE DISTRIBUTION OF THE
FINAL MODEL GROUP –
SEMIPERISHABLE SUBSISTENCE



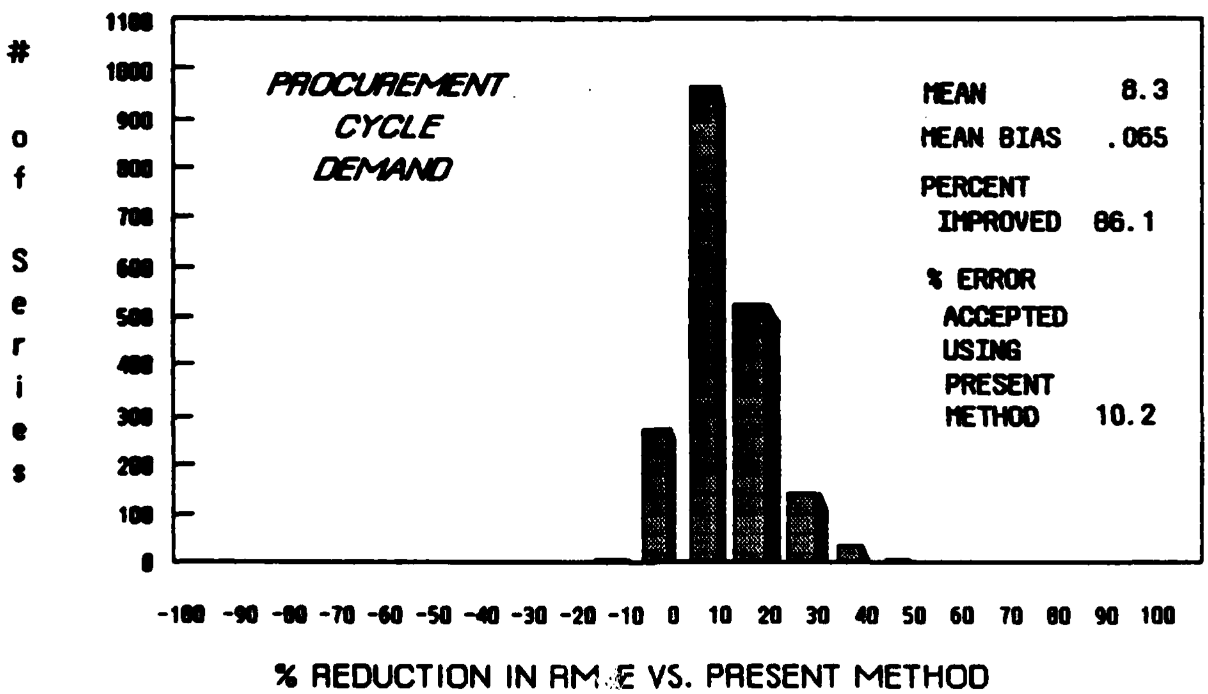
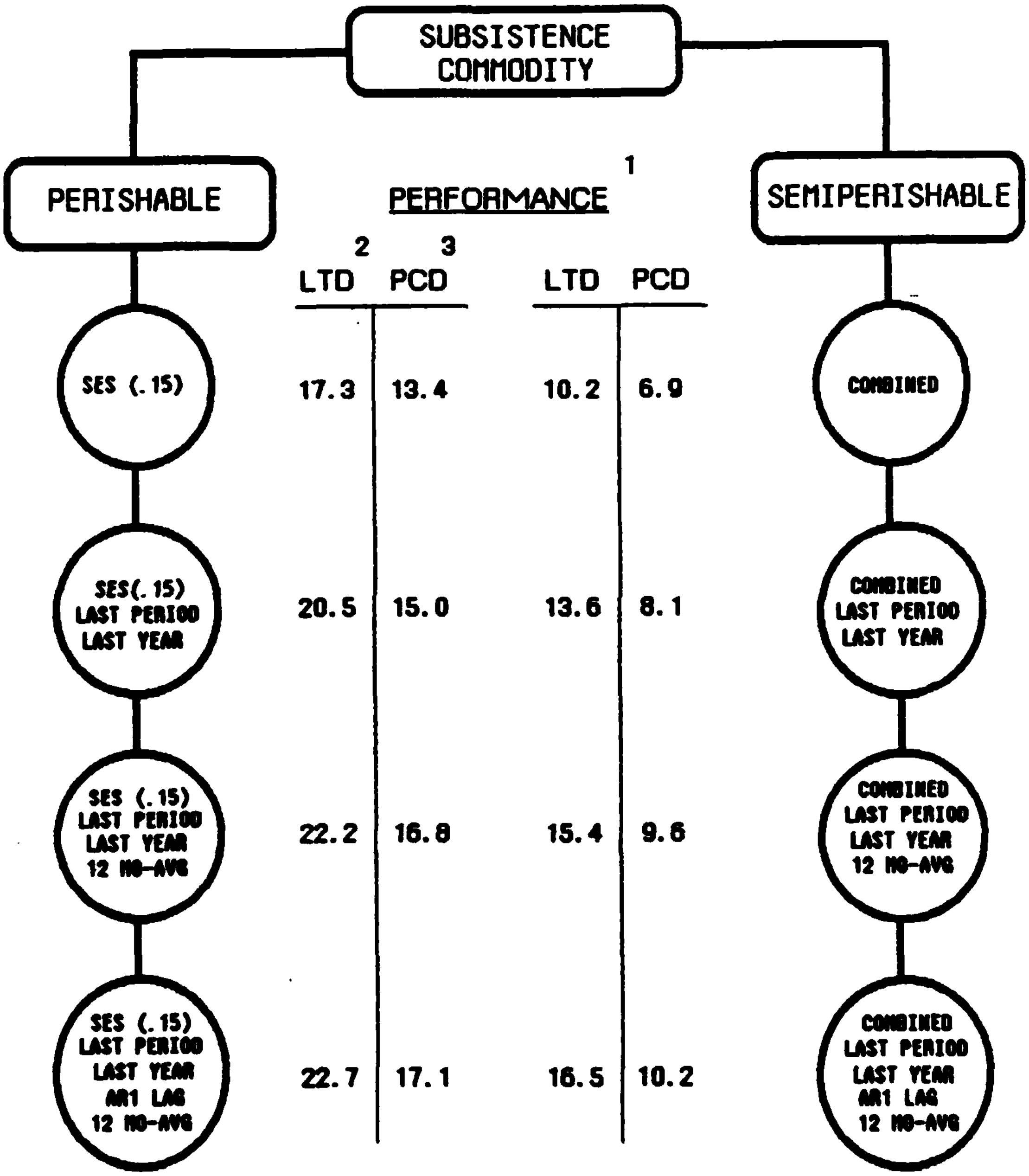


FIGURE 11

COMPARISON OF FORECAST MODEL GROUP PERFORMANCE
FOR THE SUBSISTENCE COMMODITY



[1] % ERROR ACCEPTED PRESENTLY IN LIEU OF USING NEW METHODS

[2] LEAD TIME DEMAND [3] PROCUREMENT CYCLE DEMAND

Variations in Model assignment by item characteristics are important in designing decision rules for model assignments to new items.

Tables 20 and 21 provide the frequency of occurrence of the recommended model group assignments by item category (troop issue vs brand name) for perishable and semiperishable subsistence, respectively. The final Model Group is split into Nonseasonal and Seasonal components for comparative purposes.

Table 20

FREQUENCY OF FINAL MODEL GROUP ASSIGNMENT BY ITEM CATEGORY: PERISHABLE SUBSISTENCE

Lead Time Demand

ITEM CATEGORY	% of Total Perishable Sample	Mean Reduction in RMSE	Percent Improved
TROOP ISSUE			
Nonseasonal	64.2	17.4	95.9
Seasonal	4.9	23.5	94.8
Total	69.1	17.9	95.5
BRAND NAME			
Nonseasonal	25.4	13.7	88.5
Seasonal	5.5	17.5	91.7
Total	30.9	14.4	89.1

Procurement Cycle Demand

ITEM CATEGORY	% of Total Perishable Sample	Mean Reduction in RMSE	Percent Improved
TROOP ISSUE			
Nonseasonal	65.3	12.2	92.7
Seasonal	3.8	19.9	85.7
Total	69.1	12.5	92.3
BRAND NAME			
Nonseasonal	27.3	13.0	94.5
Seasonal	3.6	21.5	97.2
Total	30.9	15.5	94.8

Table 21

FREQUENCY OF FINAL MODEL GROUP ASSIGNMENT BY ITEM CATEGORY: SEMIPERISHABLE SUBSISTENCE

Lead Time Demand

ITEM CATEGORY	% of Total Perishable Sample	Mean Reduction in RMSE	Percent Improved
TROOP ISSUE			
Nonseasonal	49.8	13.6	95.7
Seasonal	7.8	31.4	100.0
Total	57.6	16.0	96.3
BRAND NAME			
Nonseasonal	31.9	5.7	79.1
Seasonal	10.5	13.2	92.1
Total	42.4	7.5	82.3

Procurement Cycle Demand

ITEM CATEGORY	% of Total Perishable Sample	Mean Reduction in RMSE	Percent Improved
TROOP ISSUE			
Nonseasonal	51.4	10.6	92.6
Seasonal	6.2	16.8	98.3
Total	57.6	11.3	93.3
BRAND NAME			
Nonseasonal	36.8	3.5	74.1
Seasonal	5.6	9.7	90.8
Total	42.4	4.3	76.3

Tables 20 and 21 indicate that Seasonal Models generally provide from 27 to 277% better forecasts than their nonseasonal counterparts on their assigned subclasses. This is not surprising as the present DLA forecast does not consider seasonal patterns. Also, forecast performance for the troop issue category exceeded that for brand name, with the exception of procurement cycle demand for perishable items. Seasonality is most prevalent in the Semiperishable brand name category (25%) yet rare in the Perishable troop issue area (7%).

Tables 22 and 23 indicate that seasonality is most prevalent at lead times of four months for the perishable class and five months for the semiperishable class.

Figure 12 highlights the distribution assignments of the seasonal component of the final model group for the subsistence commodity.

Table 22

FREQUENCY OF FINAL MODEL GROUP ASSIGNMENTS BY LEADTIME DURATION

Perishable Subsistence

LT Duration	% of Total Perishable Sample	% of Items Assigned to Model Type Nonseasonal	Seasonal
2	8.2	94	6
3	58.9	92	8
4	32.9	84	16
MEAN 3.25	100.0	89	11

Semiperishable Subsistence

LT Duration	% of Total Semiperishable Sample	% of Items Assigned to Model Type Nonseasonal	Seasonal
4	9.0	93	7
5	44.8	75	25
6	23.7	87	13
7	10.2	81	19
8	12.2	87	13
9	0.1	100	0
10	0.0	100	0
MEAN 5.72	100.0	82	18

FIGURE 12

FREQUENCY OF OCCURRENCE OF DEMAND SEASONALITY IN THE SUBSISTENCE COMMODITY

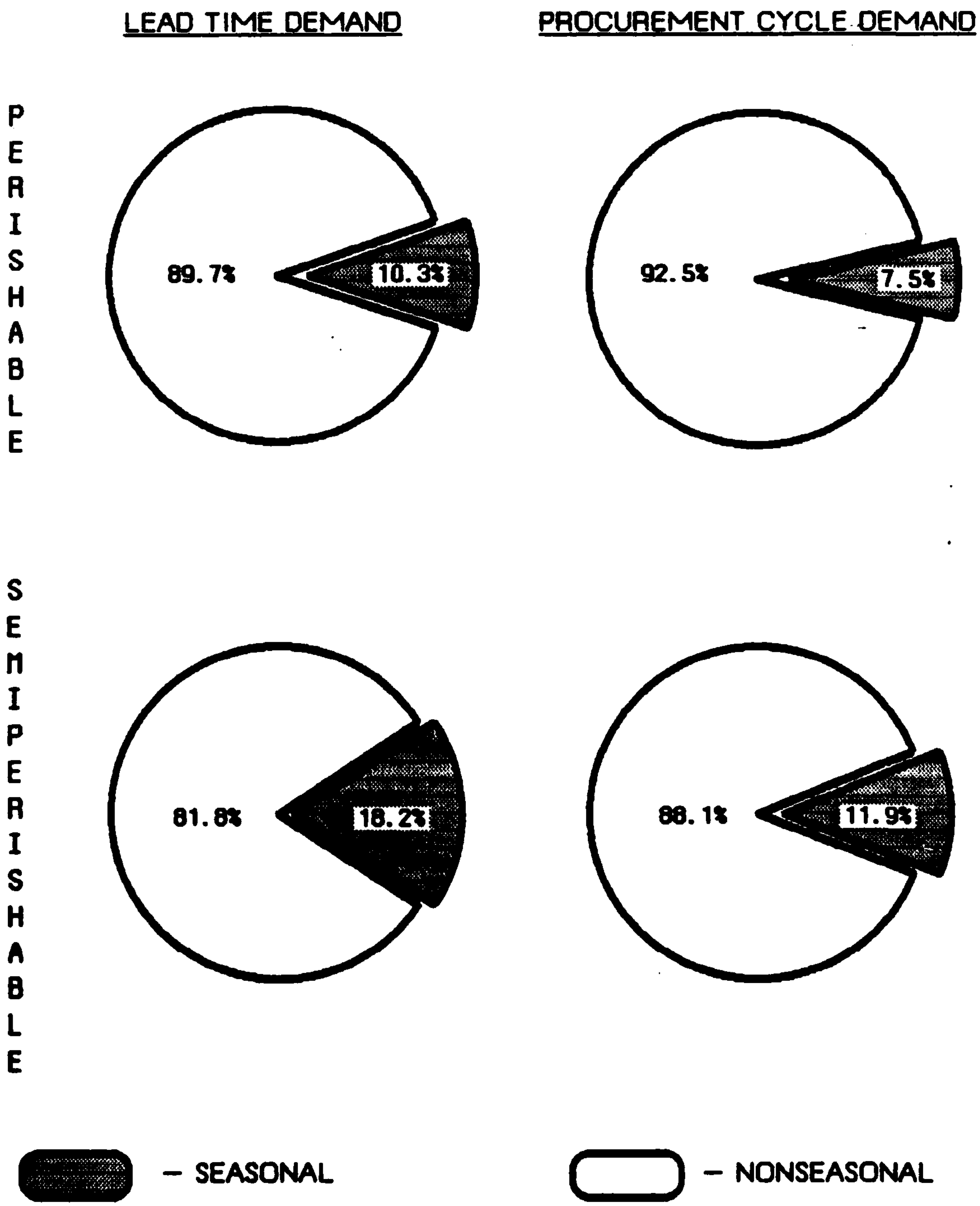


Table 23

FREQUENCY OF FINAL MODEL GROUP ASSIGNMENTS BY PROCUREMENT CYCLE DURATION

Perishable Subsistence

PC Duration Months	% of Total Perishable Sample	% of Items Assigned to Model Type Nonseasonal	Seasonal
1	100.0	93	7
MEAN 1	100.0	93	7

Semiperishable Subsistence

PC Duration Months	% of Total Semiperishable Sample	% of Items Assigned to Model Type Nonseasonal	Seasonal
1	48.1	89	11
3	50.4	89	11
4	1.3	80	20
6	0.2	100	0
MEAN 2.06	100.0	88	12

G. Areas for Further Study

Two Stage Forecasting. The authors tested two stage forecasting discussed, in Appendix C, where the forecast are adjusted for patterns in the errors. The results were promising, however, the technique can not be applied indiscriminately. When applied across all perishable items the adjusted forecasts were less accurate than the unadjusted forecasts. However, for many series the adjusted forecasts achieved 30 to 50% improvement over the unadjusted forecasts. No conclusions can be drawn without further study. The benefits of Two Stage Forecasting must be weighed against the additional data storage costs incurred. Properly applied, it may well be a valid means to achieve improved forecasting.

IV. A PROTOTYPE SUBSISTENCE DEMAND FORECASTING SYSTEM

A. Design of the Forecasting System

This section of the report describes the design of a prototype subsistence demand forecasting system based on the forecast model groups developed in Section III.

The subsistence demand forecasting system must generate a wide range of forecasts to include:

1. Fixed Forecasts (e.g., Service Requirements, Provisioning)

2. Forecast Models with Fixed Parameters (e.g., SES(.20))

3. A procedure to switch parameters and model type measure within the system based on a performance

The forecasting models in the system will be based on the final model groups in Section III with the exception that SES(.20) will be substituted for SES(.15) for perishable subsistence. The models which generate forecasts in the system are as follows:

12-MO AVG	DLA(.20)
SES(.10)	DLA(.30)
SES(.20)	LAST LT/PC
SES(.30)	LAST YEAR
DLA(.10)*	AR1 LAG

Figure 13 depicts a schematic diagram of a prototype subsistence demand forecasting system.

A description of each component of the system follows:

1. Demand History - DPSC presently has over 100 months of subsistence demand history available. Forty-eight (48) months of demand history are required to initilize the forecasting system. The most recent 24 months of demand history should be maintained on-line to compute the two naive forecasts and the 12-MO AVG forecast. Each month as a new demand is received, the on-line and off-line history files are updated.

2. Forecast Processor - The function of the forecast processor is to provide a forecast of the item/warehouse demand over the next lead time and procurement cycle. The forecast processor is divided into three subsystems as follows:

   a. Forecast Generator,

   b. Forecast History, and

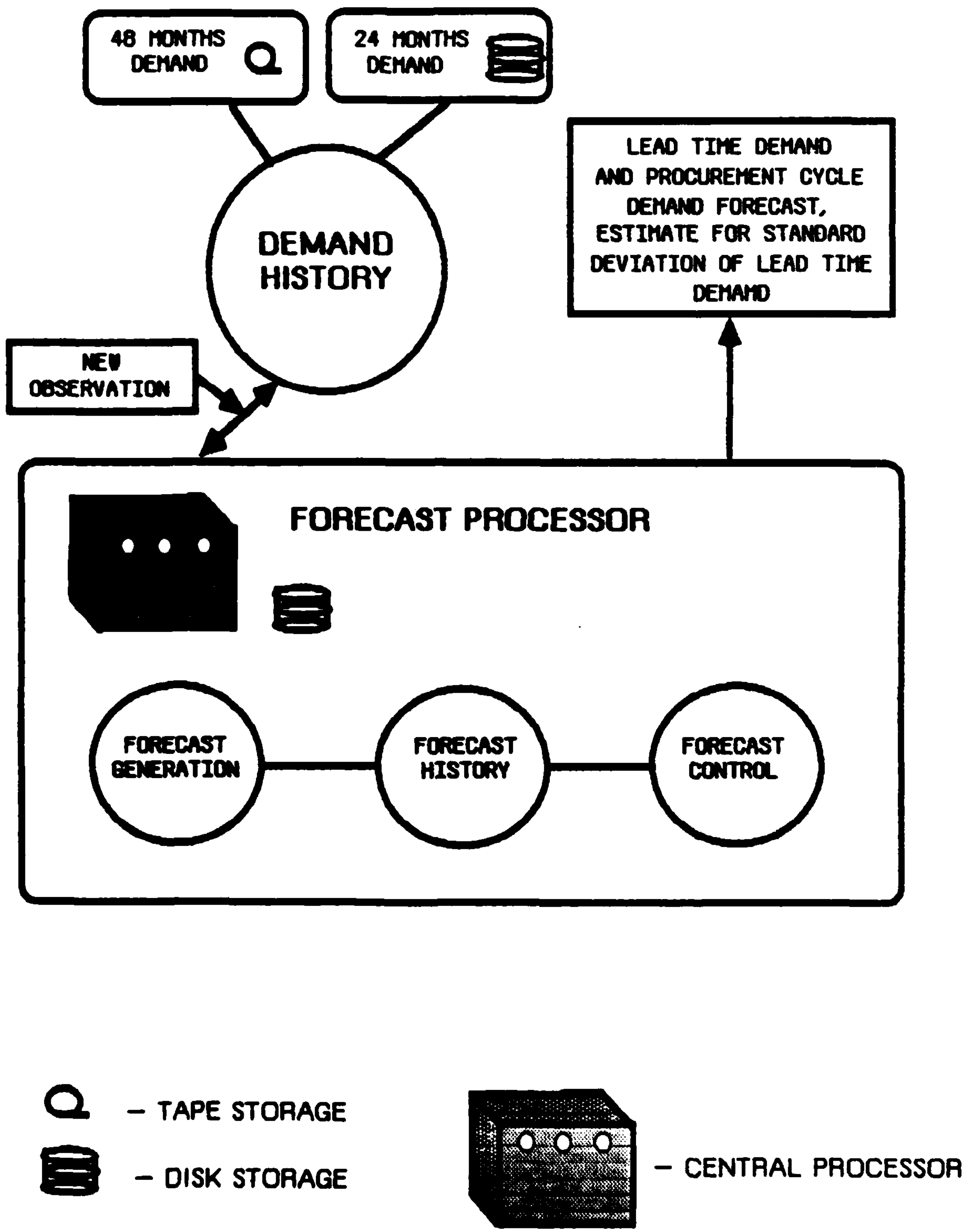
   c. Forecast Control.

The function of the forecast generator is to develop candidate forecasts for the next lead time and procurement cycle demand.

* The DLA formula, is characterized as the one-month-ahead double exponential smoothed forecast multiplied by the lead time or procurement cycle in months

FIGURE 13

SCHEMATIC OF PROTOTYPE
SUBSISTENCE DEMAND FORECASTING SYSTEM



The following values are stored in the Forecast Generator to develop forecasts for single exponential smoothing, the DLA formulation and the AR1 Lag Model:

<u>The Single Smoothed Average of Monthly Demands</u>

$S^1(.1)$, $S^1(.2)$, $S^1(.3)$

<u>The Double Smoothed Average of Monthly Demands</u>

$S^2(.1)$, $S^2(.2)$, $S^2(.3)$

<u>Summations to Compute AR1 Lag Forecast</u>

$\Sigma(F^{LM})^2, \Sigma(F^{LY})^2, \ \Sigma(F^{LM}F^{LY}), \ \Sigma F^{LM}ACT, \ \Sigma F^{LY}ACT$

where: F^{LM} = Naive Monthly Forecast (i.e., current month's demand)

F^{LY} = Naive Last Year Forecast

ACT = Actual Demand over Lead Time or Procurement Cycle

Σ = Summation over the number of periods of historical demand which are maintained

Suppose S is an item with a lead time of 5 months and procurement cycle of 3 months. Let $X_{12}, \ldots, X_2$ be the most recent 11 months of on-line demand history and let X_1 be the current month's demand.

The AR1 LAG lead time demand forecast is generated solving the following equations for a_1 and a_2:

$$a_1 (F^{LM})^2 + a_2 F^{LM}F^{LY} = (ACT)F^{LM}$$

$$a_1 F^{LM}F^{LY} + a_2 (F^{LY})^2 = (ACT)F^{LY}$$

using their values stored on the file and the current month's demand. The next AR1 LAG lead time demand forecast is:

$$F^{LAG}_{LTD} = a_1 F^{LM} + a_2 F^{LY}_{LTD}$$

$$= a_1 X_1 + a_2 (X_{12} + X_{11} + X_{10} + X_9 + X_8)$$

The five summations are updated and stored.

When the current month's demand is recorded, the single and double smoothed averages are updated by the formulae:

$$\text{New } S^1(\alpha) = \alpha X_1 + (1 - \alpha) S^1(\alpha)$$

$$\text{New } S^2(\alpha) = \alpha (\text{New } S^1(\alpha)) + (1 - \alpha) S^2(\alpha)$$

and stored. The single and DLA formulations are then generated, for example:

$$F_{LTD}^{SES(\alpha)} = LT * [NEW\ S^1(\alpha)]$$

$$F_{LTD}^{DLA(\alpha)} = LT * \left[(2 + \frac{\alpha}{1-\alpha})\ NEW\ S^1(\alpha) - (1 + \frac{\alpha}{1-\alpha})\ NEW\ S^2(\alpha)\right]$$

The 24 months of on-line demand history are used to generate the 12 month average and naive forecasts.

$$F_{LTD}^{12\text{-}MO\ AVG} = LT * \frac{X_{12} + X_{11} + \cdot \cdot \cdot + X_1}{12} = \frac{5}{12} \sum_{i=1}^{12} X_i$$

$$F_{PCD}^{12\text{-}MO\ AVG} = PC * \frac{X_{12} + X_{11} + \cdot \cdot \cdot + X_1}{12} = \frac{3}{12} \sum_{i=1}^{12} X_i$$

$$F_{LTD}^{LAST\ LT} = X_5 + X_4 + X_3 + X_2 + X_1$$

$$F_{PCD}^{LAST\ PC} = X_3 + X_2 + X_1$$

$$F_{LTD}^{LAST\ YEAR} = X_{12} + X_{11} + X_{10} + X_9 + X_8$$

$$F_{PCD}^{LAST\ YEAR} = X_7 + X_6 + X_5$$

The Forecast History File provides a holding area for forecasts to be used in future forecast control. The ten forecasts:

$F^{12\text{-}MO\ AVG}$, $F^{SES(\alpha)}$, $F^{DLA(\alpha)}$, $F^{LAST\ YEAR}$, $F^{LAST\ LT/PC}$, F^{LAG},

where: α = .1, .2, .3

for both lead time and procurement cycle are stored in the Forecast History File until the actual lead time and procurement cycle errors can be calculated. For example, when the actual lead time demand becomes available, the ABSOLUTE $ERROR_{LTD} = | F_{LTD} - A_{LTD} |$ is computed and passed to the Forecast Control File for the ten models.

The Forecast Control Processor is used to control the forecast selection process and provide an estimate for the standard deviation of lead time demand.

In Section III, tracking in the COMBINED model based on the smoothed MAD of .2, delivered the best forecast performance. The smoothed MAD of .2 is defined as

the single exponentially smoothed average (α=.2) of the absolute errors. The smoothed MAD will be denoted as SMAD(.2) and is defined recursively by:

NEW SMAD(.2) = (.2)[NEW ABS(ERROR)] + .8 [OLD SMAD(.2)]

Due to its fine performance in controlling the COMBINED model in Section III, the SMAD(.2) method is recommended as the performance criteria for forecast selection within the Forecast Control Processor. The ten values stored in the Forecast Control Processor are as follows:

Model	Control Parameter
12-MO AVG	^{1}SMAD(.2)
SES(.1)	^{2}SMAD(.2)
SES(.2)	^{3}SMAD(.2)
SES(.3)	^{4}SMAD(.2)
DLA(.1)	^{5}SMAD(.2)
DLA(.2)	^{6}SMAD(.2)
DLA(.3)	^{7}SMAD(.2)
LAST LT/PC	^{8}SMAD(.2)
LAST YEAR	^{9}SMAD(.2)
AR1 LAG	^{10}SMAD(.2)

Each month, as a new absolute error is passed to the Forecast Control Processor, the SMAD's are updated and the forecast with the least SMAD is chosen as the forecast for the next lead time or procurement cycle demand. An estimate for the standard deviation of lead time demand must be computed and is given by 1.25 * SMAD(.2) for the chosen model.

B. System Initialization. Initialization of the system is necessary to provide initial values for the exponential smoothing and AR1 Lag model of the monthly demands and of the absolute errors. Initilization involves the use of the off-line data base. Suppose that initialization is to begin at time t. For the range of smoothing constants employed in the system, the arithmetic average of the monthly demands, 13 to 24 months ago, will serve as an initial value. The arithmetic average of the absolute errors, 1 to 12 months ago, will serve as an initial value for the SMAD calculation. Monthly demands from month 48 through 13 should be used to develop the summations for the AR1 LAG calculations. The arithmetic average, 1 to 12 months ago, can serve as the initial value for the 12-MO AVG, and naive models.

C. Decision Rules for Forecast Model Assignments to the Subsistence Commodity. Table 24 provides the model assignments for the subsistence commodity.

Table 24

DECISION RULES FOR FORECAST MODEL ASSIGNMENTS TO ITEM GROUPS IN THE SUBSISTENCE COMMODITY

Established Items	
Perishable	Semiperishable
Appendix J	Appendix L
Cross Reference Listing Sorted by Stock Number	Cross Reference Listing Sorted by Stock Number
Appendix K	Appendix M
Item Groups Sorted by Model Assignment	Item Groups Sorted by Model Assignment

New Items	
0 - 24 Months	
Service Requirement (Fixed Forecast)	
24 Months and Older	
Perishable	Semiperishable
Initially SES(.2) then, switch between all models in forecast system based on smoothed MAD (.2).	Initially SES(.2) then, switch between all models in forecast system based on smoothed MAD (.2).

D. Implementation Considerations

The subsistence demand forecasting system must provide lead time and procurement cycle demand forecasts for about 4,000 item/warehouse records each month. The monthly updates can easily be run on DPSC mainframe computers within a 4-hour period. With modern breakthroughs in data storage and retrieval, the Forecasting System Storage Requirement is minimal, at worse.

The Forecast System provides DLA with the capability to identify, compare, and evaluate the various demand patterns encountered in the subsistence commodity. It also controls the demand forecasts when the demand pattern changes.

V. CONCLUSIONS AND RECOMMENDATIONS

A. Conclusions

o Seasonality is an important factor in subsistence demand forecasting . Seasonality of lead time demand occurs about 14% of the time for centrally stocked Subsistence items. Seasonality is more prevalent in the semiperishable (18%) versus perishable (10%) category. Improvements in forecast accuracy were generally much greater for items with seasonal patterns than for those with nonseasonal patterns (Tables 20 and 21).

o Demand forecasting for nonseasonal subsistence items can be significantly improved . Although the larger reduction in forecast error can be achieved for seasonal items, a reduction can also be achieved for nonseasonal items (Tables 20 and 21). The nonseasonal component of the Final Model group

reduced forecast error (measured by RMSE) by 14.7% over the lead time and 11.6% over the procurement cycle for nonseasonal perishable items. For nonseasonal semiperishable items, the reductions were 8.6% and 6.7%, respectively.

o Reduction in safety levels and "stockout cost" are possible. Reductions in the standard deviation of lead time demand will surely reduce the safety level stock held for subsistence recently valued at around $95 million (end FY 84). Also the costs of "stockout", both tangible such as special processing and impact on substitute item demand and intangible, such as customer satisfaction, will be more easily managed.

o A Forecasting System based on a group of models tested in this study can identify, compare, evaluate, and control subsistence demand patterns. Section IV describes a prototype forecasting system for the subsistence commodity. This system is based on a blend of theoretical and practical considerations. The system is designed to provide fixed forecasts, forecasts based on models with fixed parameters, and forecasts selected by performance measure. The system is relatively simple and easy to implement.

B. Recommendations

o The Executive Director for the Directorate of Supply Operations should take the following actions as a result of this study:

oo Direct that the prototype Forecasting System designed in this report be used as the basis for the Functional Description under the Defense Integrated Subsistence Management System (DISMS). Identity resources for the purposes of implementation and monitor performance.

oo Direct the incorporation of the prototype Forecasting System into the existing subsistence requirements computation system. This would serve as an independent validation of the Forecasting System and lend credence to its implementation into DISMS.

oo Direct the computer software generated in the design of the Forecasting System by maintained by DISMS for future use.

END

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